

# Human and Social Capital Strategies for Mafia Network Disruption

Annamaria Ficara<sup>1</sup>, Francesco Curreri<sup>2</sup>, Giacomo Fiumara<sup>3</sup>, *Member, IEEE*, and Pasquale De Meo<sup>1</sup>

**Abstract**—Social Network Analysis (SNA) is an interdisciplinary science that focuses on discovering the patterns of individuals interactions. In particular, practitioners have used SNA to describe and analyze criminal networks to highlight subgroups, key actors, strengths and weaknesses in order to generate disruption interventions and crime prevention systems. In this paper, the effectiveness of a total of seven disruption strategies for two real Mafia networks is investigated adopting SNA tools. Three interventions targeting actors with a high level of social capital and three interventions targeting those with a high human capital are put to the test and compared between each other and with random node removal. Similar tests on artificial model networks have also been carried out. Simulations show that actor removal based on social capital proves to be the most effective strategy, by leading to the total disruption of the criminal network in the least number of steps. The removal of a specific figure of a Mafia family such as the Caporegime seems also promising in the network disruption.

**Index Terms**—Criminal network, social network analysis, disruption, social capital, human capital, simulation.

## I. INTRODUCTION

**C**RIMINAL organizations are groups that covertly engage in illegal activities to provide goods and services to gain a profit, by accomplishing achievements at the cost of other individuals, groups or societies [1]. In particular, Mafia is a criminal group defined by Gambetta as a “territorially based criminal organization that attempts to govern territories and markets” [2]. Compared to other criminal organizations, Mafia groups are structured as a collection of loosely coupled groups, which last for several generations. Each of these groups is referred to as *cosca*, *family* or *clan*.

Because of their strong resilience to disruption, such networks pose particularly hard challenges to Law Enforcement Agencies (LEAs). Herein, we borrow methods and tools from Social Network Analysis (SNA) to investigate the effectiveness

of several law enforcement interventions against two Mafia networks, based on a real-world dataset built from a major anti-mafia operation called “Montagna” which was concluded in 2007. This dataset was used in different studies on Mafia networks through SNA to analyze the structure of such networks [3], [4], identify subgroups and highlight actors in strategic positions [5], [6], [7], and develop disruption and prevention methods [8], [9], [10].

SNA is a growing interdisciplinary science that focuses on discovering the patterns of individual interactions. SNA spans through different domains such as Anthropology, Sociology, Psychology, Economics, Mathematics, Medicine and Computer Science [11].

The idea of conceiving organized crime as a network, rather than a hierarchical structure, has incrementally grown in criminologist literature over the last century. During the twentieth century, the most common approach to study organized crime was the “alien conspiracy theory”. This theory blamed the origin of crime to outsiders (hence its name) and considered it structured as a bureaucratic organization following a peculiar hierarchy with specific roles [12]. Only by the end of that century, such view was abandoned in favor of new analytical methods. They considered organized crime as a system of loosely structured relationships mainly based on patron-client relations. Investigations started to be conducted by performing link analysis through visual representations of the structure of the criminal groups [13], giving birth to the first applications of network analysis as a “tool” [14]. Already by the ’80s, network methods and concepts, such as density and centrality, were adopted to study criminal groups [13].

Social networks, including criminal networks, can thus be conceptualized as being made of two kinds of *capital*, *i.e.* human capital and social capital.

Human capital refers to the personal attributes and/or resources of the individuals within a network. It is defined as “the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being” [15].

Social capital refers to the connections or ties between the individuals in a network. It is defined as “those tangible assets that count for most in the daily lives of people: namely goodwill, fellowship, sympathy, and social intercourse among the individuals and families who make up a social unit” [15].

LEAs may be able to disrupt criminal networks by strategically targeting individuals who act like brokers or have more connections than others (*i.e.* high social capital) and specific skills or roles (*i.e.* high human capital) [16], [17].

Manuscript received 22 February 2022; revised 22 September 2022 and 11 January 2023; accepted 23 February 2023. Date of publication 13 March 2023; date of current version 23 March 2023. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Edgar Weippl. (*Corresponding author: Giacomo Fiumara.*)

Annamaria Ficara is with the Department of Cognitive Science, Education and Cultural Studies, University of Messina, 98122 Messina, Italy (e-mail: aficara@unime.it).

Francesco Curreri is with the Department of Mathematics and Computer Science, University of Palermo, 90123 Palermo, Italy (e-mail: fcurreri@unime.it).

Giacomo Fiumara is with the Department of Mathematics, Computer Science, Physics and Earth Science, University of Messina, 98122 Messina, Italy (e-mail: gfiumara@unime.it).

Pasquale De Meo is with the Department of Ancient and Modern Civilizations, University of Messina, 98122 Messina, Italy (e-mail: pdemeo@unime.it).

Digital Object Identifier 10.1109/TIFS.2023.3256706

This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License. For more information, see <https://creativecommons.org/licenses/by-nc-nd/4.0/>

For this reason, the two main strategies for criminal network disruption are divided into the two main approaches of social and human capitals.

The social capital approach requires the use of SNA which focuses on the computation for network measurements such as density and centralization, analysis of clusters and the measure of the centrality of individuals [18], [19], [20]. Centrality measures are able to identify critical actors in a criminal group [21], [22], [23], [24]. The two most common centrality measures are degree and betweenness centralities. Other measures have been proposed to maximize criminal network disruption such as network capital [20].

The human capital approach requires the identification of key roles, skills, information or resources associated with each actor.

In [25], we provided a literature review of the most significant works on covert network disruption. We underlined how disruption strategies based on human or social capitals are usually developed in a parallel fashion and exploit very different techniques. Social and human capitals can be used together thus creating a third approach which we defined as the mixed approach. Only few researchers tried this unified approach that seeks to identify nodes in the network which are simultaneously able to deteriorate both capitals [26], [27], [17], [28], [29], [30], [31], [32]. For example, Bright et al. [31] adopted different strategies based on either human or social capital exploring the validity of five LEAs' interventions in dismantling and disrupting criminal networks. We also noticed that most of the works on covert network disruption refer to terrorist networks while there are very few papers about Mafia network disruption. For this reason and inspired by [31], in this paper, we introduced and tested on our Mafia networks different disruption strategies based on either human and social capitals. We used three traditional centrality measures to target actors with a high level of social capital: degree, betweenness and closeness centralities. We also selected caporegimes, soldiers and entrepreneurs as targeted actors with a high level of human capital. At each step, an actor is removed and the network integrity is evaluated through three measures, namely the number of connected components, the size of the largest connected component and the average global efficiency. Such interventions are then compared with each other and with random removal of actors for both networks, leading to a total of seven different strategies. The random strategy is an important comparison since it can be seen as the case in which LEAs randomly raid sites of illegal actions making arrests on the spot. The aim is to gain insights about the most efficient disruptive strategy, that is evaluated by the number of steps before the complete disruption and consistency above replications.

Centrality metrics are effective to spot important actors in a social network but, as previous theoretical studies have shown [33], they could be insufficient to detect the key players in a criminal organization as well as to predict criminal events. Specifically, Varese [34] studied a Russian Mafia outpost operating in Rome and he discovered a high degree node corresponding to an individual on the payroll

of the gang but who did not belong to the gang; such an individual acted as an intermediary between the gang leader and the Roman underworld. Campana [35] built a network depicting human trafficking between Italy and Nigeria; from this research work, we highlight two types of actors, namely transporters and exploiters. Surprisingly enough, the exploiters display the lowest degree, although they can be regarded as the main perpetrators of human trafficking activities. Our study is thus a first step to combine methods from SNA (and, in particular, centrality metrics) with actor attributes to quantify the effectiveness of various dismantling strategies; however, we fully acknowledge the limitations due to the usage of centrality metrics as the sole tool to measure the social capital of a Mafia gang. We leave as future work the exploitation of further network parameters to better quantify the social capital associated with a criminal organization.

Bright et al. [31] considered a case study related to the manufacture and trafficking of synthetic drugs like methamphetamine. The actors within the derived network must possess specific resources to perform their duties and carry out the process of drug cultivation, production, and distribution. These resources are drugs, precursor chemicals, equipment, money, premises, skills, labor and information. The human capital strategy was implemented by removing actors possessing a particular resource and the highest degree centrality value. Our approach is different because our aim is to dismantle Mafia families, which have a very peculiar hierarchical structure [5], with different characteristics from simple criminal groups who produce and distribute synthetic drugs. In fact, our human capital strategy does not consist in targeting actors who possess a particular resource but those who have a particular role in the hierarchy of the Mafia group. Then, we want to verify if it is possible to create a network model for criminal network disruption using an artificial network with the same characteristics of a Mafia network. In our previous work [4], we used some popular network models like the Erdős-Rényi (ER) [36] model, the Watts-Strogatz (WS) [37] model and different configurations of the Barabási-Albert (BA) [38] model to replicate the topology of a criminal network. Our experiments identified the BA model as the one which better represents a criminal network. Once we have identified the key role in the hierarchy of a Mafia family or in its criminal activities, we want to try to identify this role in BA models and apply our disruption strategies to these models. Specifically, the human capital approach is simulated targeting nodes with the same rank of the caporegimes in our Mafia networks.

The paper is structured as follows. In Section II, the dataset adopted in this work is introduced. In Section III we describe all the seven disruption strategies, divided into three categories: social capital, human capital and random actor removal; the algorithms for the simulations are explained; measures to evaluate the network integrity are given as well. In Section IV are shown the results and comparison between the methods applied on Mafia networks and BA models. Section V discusses the main limitations due to the adoption of centrality metrics in the analysis of a criminal organization.

We draw our conclusions and illustrate future research avenue we plan to explore in Section VI.

## II. CRIMINAL NETWORK DATASET

Our analysis focuses on two real criminal networks related to a specific anti-mafia operation called Montagna [9], [10], [4], [5], [6], [8].

This operation was conducted by the Special Operations Group (ROS) of the Italian Carabinieri and the Provincial Command of Messina (Sicily) who were able to eliminate leaders of the Mistretta family and the Batanesi clan (operating in Tortorici) making 39 arrests under preventive detention orders and reporting 28 suspected criminals on the loose. The Mistretta family and the Batanesi clan, between 2003 and 2007, monopolized the sector of public contracts in the Tyrrhenian strip and in the nebroidal district of the province of Messina, through a cartel of entrepreneurs close to the Sicilian Mafia. Between the end of the '90s and the beginning of the 2000s, these entrepreneurs acquired important public orders, from supplies for works on roads and highways to contracts for the methanization of many municipalities in the area. Furthermore, the Montagna operation identified the Mistretta family as a mediator between Mafia families in Palermo and Catania and other criminal organizations around Messina.

In 2007, after the conclusion of the anti-mafia operation, a pre-trial detention order for 38 individuals was issued by the Preliminary Investigation Judge of Messina. It was a two hundred pages document which contained a lot of details about crimes, activities, meetings, and calls among the suspected criminals. From this order, we extracted two unique undirected and weighted networks, *i.e.* Montagna Meetings  $M_M$  and Montagna Phone Calls  $M_{PC}$ . The first one contains 101 suspected criminals close to the Sicilian Mafia connected by 256 links which represent meetings emerging from the police physical surveillance. The second one contains 100 suspects connected by 124 links which represent phone calls emerging from the police audio surveillance.  $M_M$  and  $M_{PC}$  share 47 nodes and are available on Zenodo [39].

As we have already discussed in [5], a Mafia family or clan has a typical hierarchical structure. On top of the pyramid hierarchical chart is the Boss who keeps a low profile often hiding his real identity. He makes all the major decisions, controls the other members of the clan and resolves any kind of dispute. Just below him is the Underboss who is the second in command. If the Boss risks going to jail or is pretty old, the Underboss can replace him and resolve some disputes without involving him. In-between the Boss and Underboss there are two key roles which are the Consigliere and the Messaggero. The first one advises the boss and makes fair decisions for the good of the Mafia. The second one is a messenger who limits the public exposure of the boss, reducing the need for sit-downs or meetings between the clans. In a specific geographical location, the Caporegime or Capo manages his group of criminals within the family. He is just below the underboss and his career depends on the amount of money he can bring into the criminal family. The number of Caporegimes in a given family depends on the dimension

TABLE I  
LIST OF ATTRIBUTES AND NUMBER OF NODES WHO POSSESS EACH  
IN THE MEETINGS AND PHONE CALLS NETWORKS EXTRACTED  
FROM THE MONTAGNA OPERATION

Attribute	No. nodes		
	Meetings	Phone Calls	
Boss	4	0	
Messaggero	1	1	
Caporegime	12	7	
Deputy Caporegime	2	2	
Soldier	18	18	
Associate	Entrepreneur	26	25
	Pharmacist	2	2
	Lawyer	1	1
	Electrician	1	0
	City employee	0	1
	Transporter	0	2
	Cooperating witness	1	0
	Landowner	0	1
	Bar owner	0	1
	Fishmonger	0	1
	Accountant	0	1
	Breeder	2	1
	Construction worker	1	0
	External partnership	5	8
Relative	6	3	
Cohabitee	0	2	
Fugitive	1	0	
Charged	0	2	
In jail	2	3	
Figurehead	0	2	
Unclear	16	16	

of that family. A capo can have many soldiers in his crew. Soldiers are street level mobsters who essentially are no more than average criminals. Then come associates who work with Mafia soldiers and caporegimes on various criminal activities. They can be drug dealers or thieves, as well as entrepreneurs, pharmacists, lawyers, politicians or police officers, who are not actual members of the Mafia, but work with the mob.

Starting from our pre-trial detention order, we were also able to reconstruct the roles of the actors according to the specific hierarchy of Mafia families and also defining the roles of associates in our criminal networks. Thus, we built a labeled graph in which each node has an attribute as described in Table I. This attribute corresponds to the role of the node in the pyramidal hierarchical structure of Mafia clans [5]. Moreover, Table I also shows the number of nodes having that specific role in  $M_M$  and  $M_{PC}$  networks, respectively. In both networks, most of the nodes are entrepreneurs. The role of an associate as an entrepreneur is important for Mafia families to win public tenders and to accomplish the public contracts in a fraudulent way. Many nodes also belong to the categories of soldiers and caporegimes. Soldiers are also important because they are those who actually commit crimes such as robbery, extortion and arson attacks. Then, caporegimes have a significant role in both the Batanesi and Mistretta families having the major social status and influence in the criminal organization. They command their crews of soldiers and report directly to the Boss or the Underboss. The identification of specific roles is important for the development of human capital strategies for network disruption. Although in principle all roles should be considered

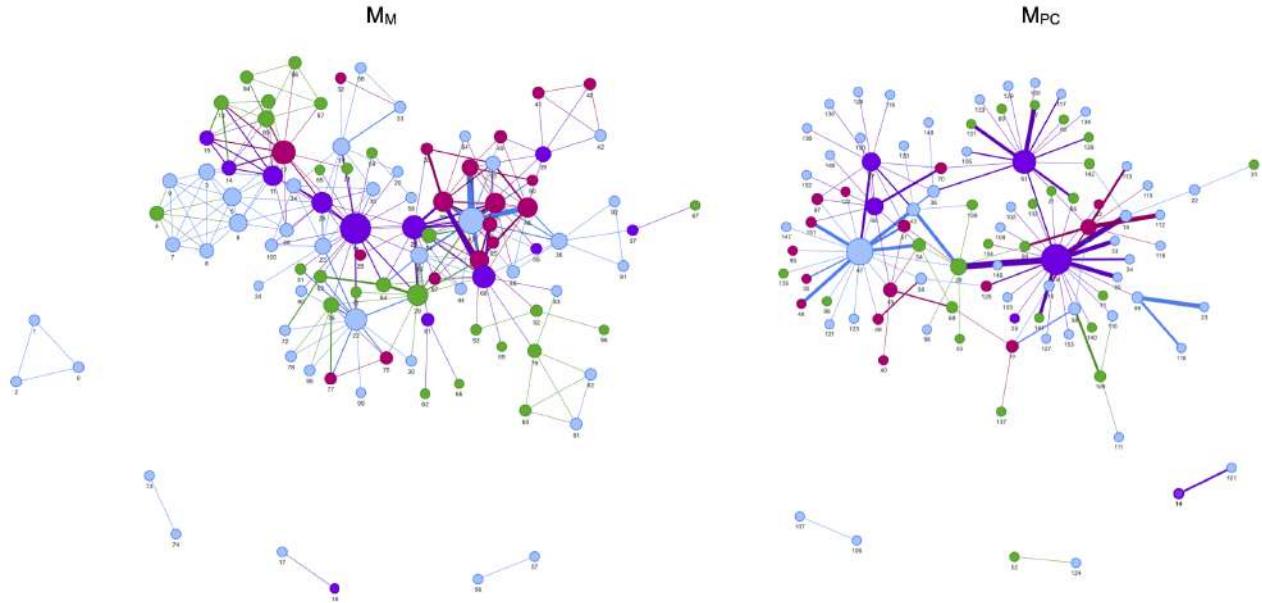


Fig. 1. The Montagna Meetings  $M_M$  and Phone Calls  $M_{PC}$  networks. The edge width is equal to the edge weights, *i.e.* the number of meetings (or phone calls). The node size is proportional to node degree. Caporegimes are marked in purple, soldiers in burgundy and entrepreneurs in green.

in network disruption experiments, in practice only the three more frequent were selected during our experiments, *i.e.* entrepreneur, soldiers and caporegimes (see Subsect. III-C). This reflects also in Algorithms 3, in which only these three roles have been considered.

In Figure 1, caporegimes, soldiers and entrepreneurs are colored in purple, burgundy and green, respectively.

### III. CRIMINAL NETWORK DISRUPTION STRATEGIES

In our experiments we reproduce the interventions that LEAs usually carry out to disrupt and dismantle criminal networks, that is to say we remove a node and all the incident edges. The nodes are selected according to their human and social capital, following criteria that will be discussed in detail in Subsects. III-A and III-C. Each of these interventions is modeled by a targeting method which begins with the full networks  $M_M$  and  $M_{PC}$  respectively of 101 and 100 actors. At each time step, we (i) delete a node according to the specific targeting method, and (ii) measure the number of connected components, the size of the largest connected component, and the average global efficiency. For each intervention, the simulation stops when the network is completely disrupted: that is, when no nodes remain. For this study three general disruption approaches have been used: social capital disruption, random disruption and human capital disruption for a total of seven different disruption strategies.

#### A. Social Capital Disruption

The social capital disruption approach aims at strategic positions within criminal networks. It is described in the Algorithm 1.

Three main strategies have been used: degree centrality attack, betweenness centrality attack and closeness centrality attack.

Degree centrality attacks are implemented by removing the actors sequentially according to the maximal degree centrality. Degree centrality (DC) [40] determines the importance of an actor based on the number of connections and it is defined as

$$DC_i = \frac{d_i}{n-1}, \quad (1)$$

where  $d_i$  is the degree of the actor  $i$  and  $n$  is the number of network nodes. High degree centrality actors are called hubs because they are important for the flow of resources and information throughout the network [17]. Hubs are associated with powerful and influential positions within social networks.

Betweenness centrality attacks are implemented by removing the actors sequentially according to the maximal betweenness centrality. Betweenness centrality (BC) [41] measures how frequently a node lies on the shortest paths between other pairs of nodes:

$$BC_i = \sum_{h,k} \frac{v_{hk}^i}{g_{hk}}, \quad (2)$$

where  $v_{hk}^i$  is the number of shortest paths from the actor  $h$  to the actor  $k$  by passing through  $i$  and  $g_{hk}$  is the total number of shortest paths from  $h$  to  $k$ . BC represents the ability of some actors to control the flow of connectivity (*e.g.* information, resources etc.) within the network. Since these actors often connect otherwise poorly connected parts of the network, they are called brokers.

Closeness centrality attacks are implemented by removing the actors sequentially according to the maximal closeness centrality. Closeness centrality (CL) [40] is defined as:

$$CL_i = \frac{n}{\sum_j d_{ij}}, \quad (3)$$

where  $d_{ij}$  is the distance between  $i$  and  $j$  and  $n$  is the size of the network. CL measures how close an actor is to the

other actors in the network. This measure has the aim of measuring the ability of autonomy or independence of the actors.

---

**Algorithm 1** Social Capital Disruption
 

---

```

% Initialization;
set an undirected graph  $G = (V, E)$ ;
set the initial number of connected components  $cc_0$  of  $G$ ;
set the initial size of the largest connected component  $lcc_0$  of  $G$ ;
set the initial average global efficiency  $E_{glob}^0$  of  $G$ ;
set  $T = |V|$ , the number of steps to stop the algorithm;
for each step  $s = 1 : T$  do
  % Choose a centrality measure (Degree, Betweenness, Closeness);
  compute the centrality of each node  $n \in V$ ;
  % Apply the target strategy to disrupt  $G$ ;
  set a node  $c \in V$  as the most central;
  remove  $c$  from  $V$ ;
  % Compute the normalized number of connected components;
   $cc_s = cc_s / cc_0$ ;
  % Compute the normalized size of the largest connected component;
   $lcc_s = lcc_s / lcc_0$ ;
  % Compute the normalized average global efficiency;
   $E_{glob}^s = E_{glob}^s / E_{glob}^0$ ;
end

```

---

### B. Random Disruption

The random disruption approach follows no preference or ranking during the actor selection for removal. It is described in the Algorithm 2. This strategy can be associated with non-strategic opportunistic law enforcement interventions. This is the case in which for example law enforcement officers randomly bust sites of illicit activities and make arrests on the spot [17].

### C. Human Capital Disruption

The human capital disruption strategy consists in targeting actors with specific roles in a Mafia family. This approach is described in Algorithm 3.

Based on observations within the data under study and the literature on Mafia networks, the roles of entrepreneur, soldier and caporegime were selected to analyze this strategy.

Targeting entrepreneurs attacks are implemented by removing the actors with the specific role of entrepreneur in order of decreasing DC.

Targeting soldiers attacks are implemented by removing the actors with the specific role of soldier in order of decreasing DC.

Targeting caporegimes attacks are implemented by removing the actors with the specific role of caporegime in order of decreasing DC.

---

**Algorithm 2** Random Disruption
 

---

```

% Initialization;
set an undirected graph  $G = (V, E)$ ;
set the initial number of connected components  $cc_0$  of  $G$ ;
set the initial size of the largest connected component  $lcc_0$  of  $G$ ;
set the initial average global efficiency  $E_{glob}^0$  of  $G$ ;
set  $T = |V|$ , the number of steps to stop the algorithm;
for each step  $s = 1 : T$  do
  % Apply the random selection strategy to disrupt  $G$ ;
  randomly pick a node  $n \in V$ ;
  remove  $n$  from  $V$ ;
  % Compute the normalized number of connected components;
   $cc_s = cc_s / cc_0$ ;
  % Compute the normalized size of the largest connected component;
   $lcc_s = lcc_s / lcc_0$ ;
  % Compute the normalized average global efficiency;
   $E_{glob}^s = E_{glob}^s / E_{glob}^0$ ;
end

```

---



---

**Algorithm 3** Human Capital Disruption
 

---

```

% Initialization;
set an undirected graph  $G = (V, E)$ ;
add customized labels on  $G$  nodes according to Table I;
set  $S \subset V$  as a subset of nodes with a specific label (Entrepreneur, Soldier, Caporegime);
set the initial number of connected components  $cc_0$  of  $G$ ;
set the initial size of the largest connected component  $lcc_0$  of  $G$ ;
set the initial average global efficiency  $E_{glob}^0$  of  $G$ ;
set  $T = |S|$ , the number of steps to stop the algorithm;
for each step  $s = 1 : T$  do
  % Compute centrality;
  compute the degree centrality of each node  $n \in S$ ;
  % Apply the target strategy to disrupt  $G$ ;
  set a node  $c \in S$  as the most central;
  remove  $c$  from  $S$ ;
  % Compute the normalized number of connected components;
   $cc_s = cc_s / cc_0$ ;
  % Compute the normalized size of the largest connected component;
   $lcc_s = lcc_s / lcc_0$ ;
  % Compute the normalized average global efficiency;
   $E_{glob}^s = E_{glob}^s / E_{glob}^0$ ;
end

```

---

### D. Disruption Effects on Criminal Network Structure

As portrayed in Algorithms 1, 2, 3, after each actor removal performed following our three disruption strategies, we want to measure the impact of our attacks on the networks structure in terms of connectivity and efficiency. Therefore the following metrics have been used: (1) the number of connected

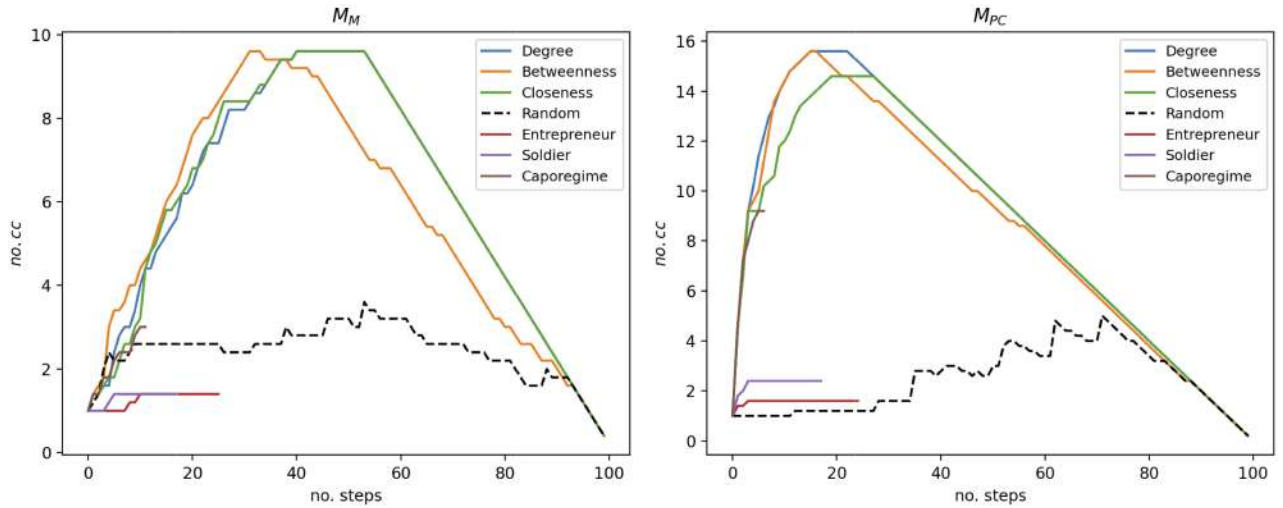


Fig. 2. Number of connected components in Montagna Meetings and Montagna Phone Calls networks.

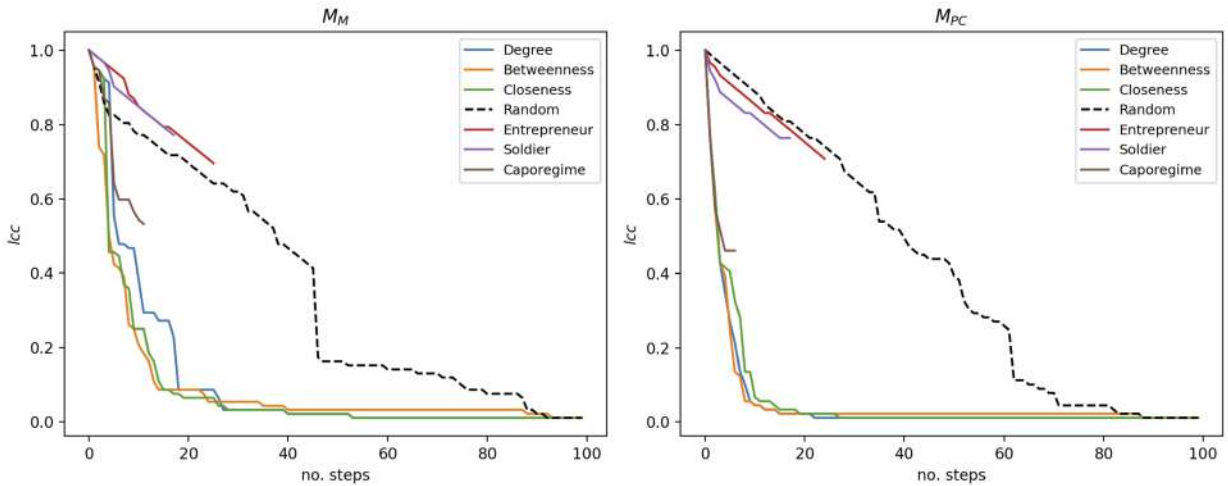


Fig. 3. Largest connected component in Montagna Meetings and Montagna Phone Calls networks.

components  $cc$ ; (2) the largest connected component  $lcc$ ; (3) the global efficiency  $E_{glob}$ .

The connected components show the reachability within the network. In connected components, all the nodes are in fact always reachable from each other. When the number of connected components increases, the number of isolated nodes increases.

In real undirected graphs, we typically find that there is a largest connected component which fills most of the graph while the rest of the network is divided into a large number of small components disconnected from the rest.

Latora and Marchiori [42] introduced the concept of efficiency of a graph as a measure of how efficiently it exchanges information. The average efficiency of a pair of nodes  $i$  and  $j$  in a graph  $G$  is the multiplicative inverse of the shortest path distance between the nodes:

$$E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{i,j}}. \quad (4)$$

The average global efficiency of a graph is the average efficiency of all pairs of nodes.

## IV. RESULTS

To facilitate comparisons across the disruption strategies described in Subsect. III, we plot three outcome measures on three separate figures: number of connected components (see Figure 2), largest connected component size (see Figure 3), and average global efficiency (see Figure 4). For each plot, the x-axis shows the number of steps performed. At each step, one actor is removed according to the social, human or random approach.

Our results show that the social capital approach is able to increase the number of connected components, to decrease the size of the largest connected components and the network efficiency in both the Meetings and Phone Calls networks on average by step 20.

Random disruption strategy is ineffective.

The human capital approach is as ineffective as the random one or even worse when soldiers or entrepreneurs are removed. Unexpectedly, targeting based on entrepreneurs seems to be unable to disrupt the networks despite they should have a key role in the Montagna operation. Targeting based on caporegimes represents an exception because it seems to be

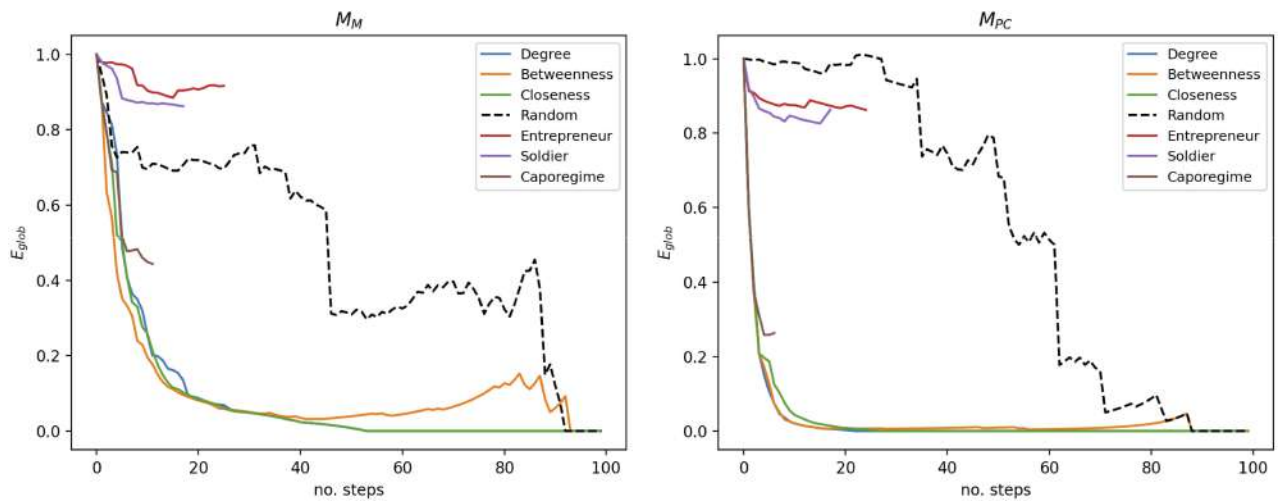


Fig. 4. Global efficiency in Montagna Meetings and Montagna Phone Calls networks.

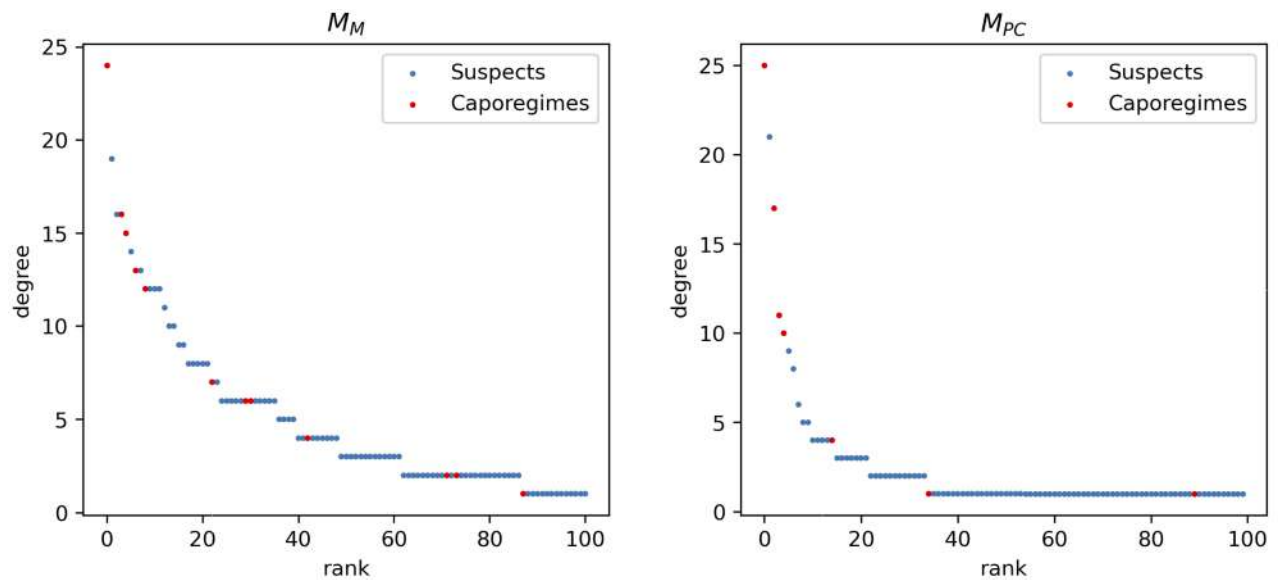


Fig. 5. Ranking nodes in Montagna Meetings and Montagna Phone Calls networks according to their degree of connectivity.

able of disrupting the networks as the degree, betweenness and closeness targeting.

Based on this good result about the removal of caporegimes, we decided to rank nodes according to their degree of connectivity, highlighting in red the caporegimes (see Figure 5).

Then, we did a different kind of analysis to know: (1) if it is possible to identify a role of a Mafia family as the caporegime on a network model based on the ranking of nodes; (2) if the application of the random, social and human capital disruption strategies is effective on a network model.

In one of our previous work [4], we used some popular network models like random networks (*i.e.* the ER [36] model), small-world networks (*i.e.* the WS [37] model), and different configurations of scale-free networks (*i.e.* the BA [38] model) to replicate the topology of our  $M_M$  network.

Since our experiments identified the BA model as the one which better represented that criminal network, in the present work we rank nodes according to their degree of connectivity

in two kinds of BA models. We highlight in red the nodes with the same rank of the caporegimes in both  $M_M$  and  $M_{PC}$  networks (*i.e.* the supposed caporegimes). A BA graph of  $n$  nodes is grown by attaching new nodes each with  $m$  edges that are preferentially attached to existing nodes with high degree. In this study, we choose  $n = 100$  and  $m = 2$  and  $m = 3$  to match their density to that of  $M_M$  and  $M_{PC}$ .

Then, we apply our disruption strategies to the BA models. We plot the three outcome measures on three separate figures: number of connected components (see Figure 7), largest connected component size (see Figure 8), and average global efficiency (see Figure 9). Our results show once again the efficiency of the social capital approach respect to the random one and how the targeting of the supposed caporegimes appears effective as the social capital approach. The efficacy of the removal of the supposed caporegimes also proves that the caporegimes are correctly identified in the network model. Moreover, the results obtained for the BA graph with  $m = 2$  are more similar to the one obtained for our criminal networks. The network in fact starts to be dismantled on

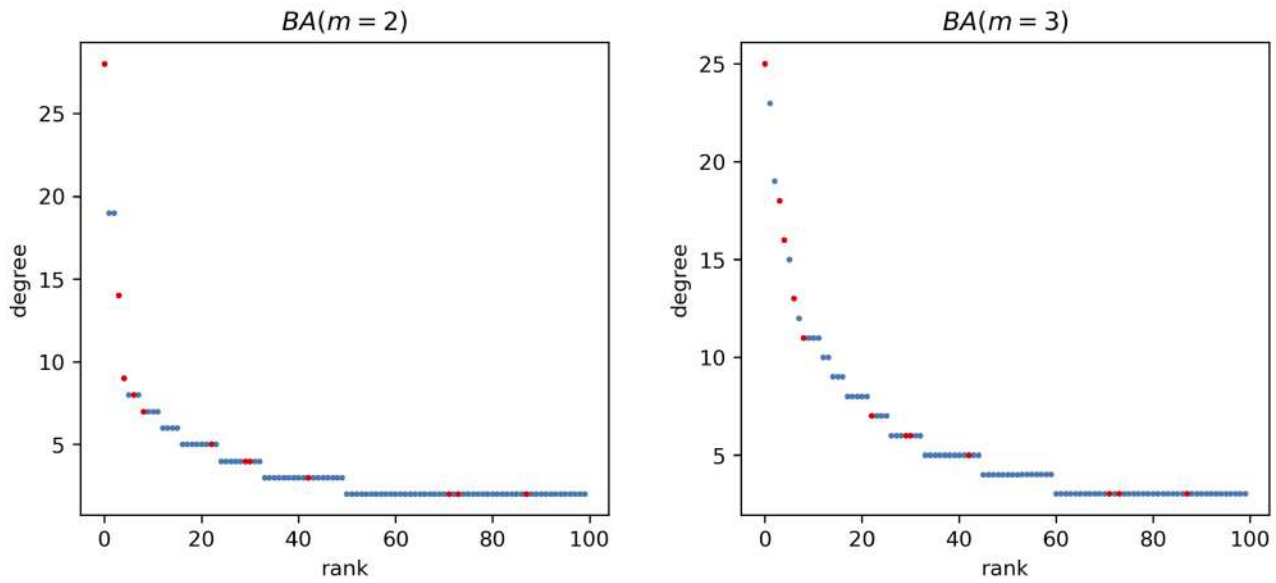


Fig. 6. Ranking nodes in Barabási-Albert models according to their degree of connectivity.

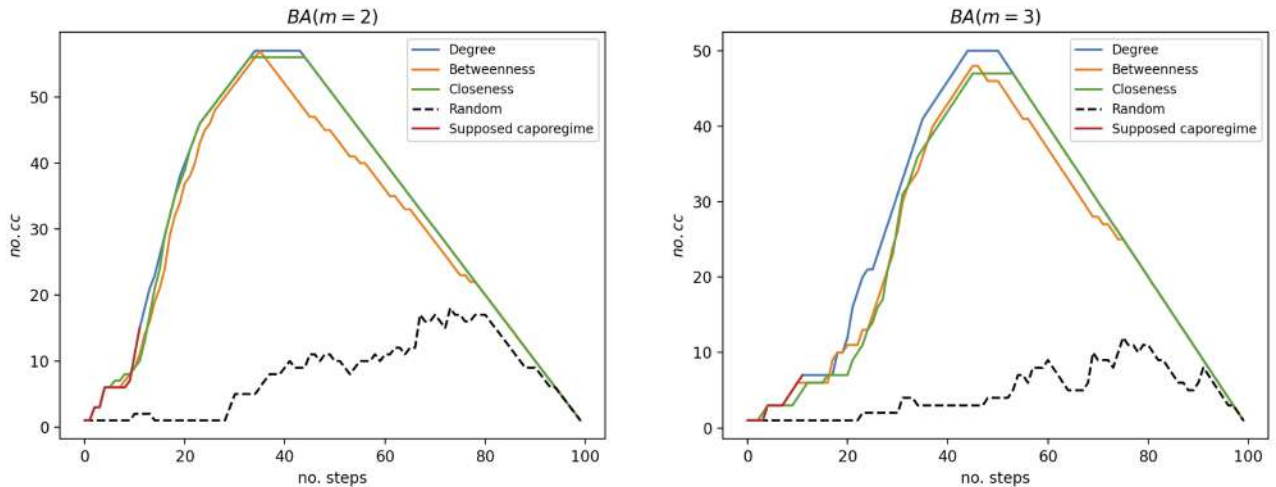


Fig. 7. Number of connected components in Barabási-Albert models.

average by step 20. The BA model with  $m = 3$  starts to be dismantled on average by step 30.

V. LIMITATIONS

As our experimental study shows, centrality metrics are effective to spot the nodes whose removal damages the most the connectivity of a criminal network. However, we acknowledge that centrality metrics alone are insufficient to quantify the social capital associated with a criminal organization as well as to predict crime events; in the worst cases, the mere application of these metrics could lead to wrong conclusions. Specifically, recent theoretical work [33] suggest that centrality metrics should be used with caution and the findings obtained with an empirical approach should be complemented by some form a qualitative knowledge [34], [35].

To clarify this point, we refer to a previous study by Varese [34], which focused on the organization and evolution of a Russian Mafia group operating in Rome. Such a group whose modeled as a network with 164 nodes; the three

largest degree nodes were labeled with the fictitious names Yakovlev, Pepe and Sergeyev and, if we would use topological information alone, we would be inclined to assume that these nodes were structurally equivalent.

However, Yakovlev was a member of the Russian Mafia who established the Russian mafia outpost in Italy. Pepe was an Italian fixer working for Yakovlev while Sergeyev was a Russian businessman involved in money laundering tasks. Despite the three nodes roughly displayed the same number of links, they had a different power in making decisions. The neighborhoods of each of the aforementioned nodes were significantly different and, thus, three distinct sub-groups of nodes were available in the network.

A further example is due to Campana [35] who built a network describing human trafficking between Nigeria and Italy. In such a network, node degree indicates the level of participation of an individual in trafficking activities and, thus, one would be tempted to conclude that high degree nodes are also the key players in trafficking crimes. The neighborhood of each of the nodes we mentioned above were also significantly



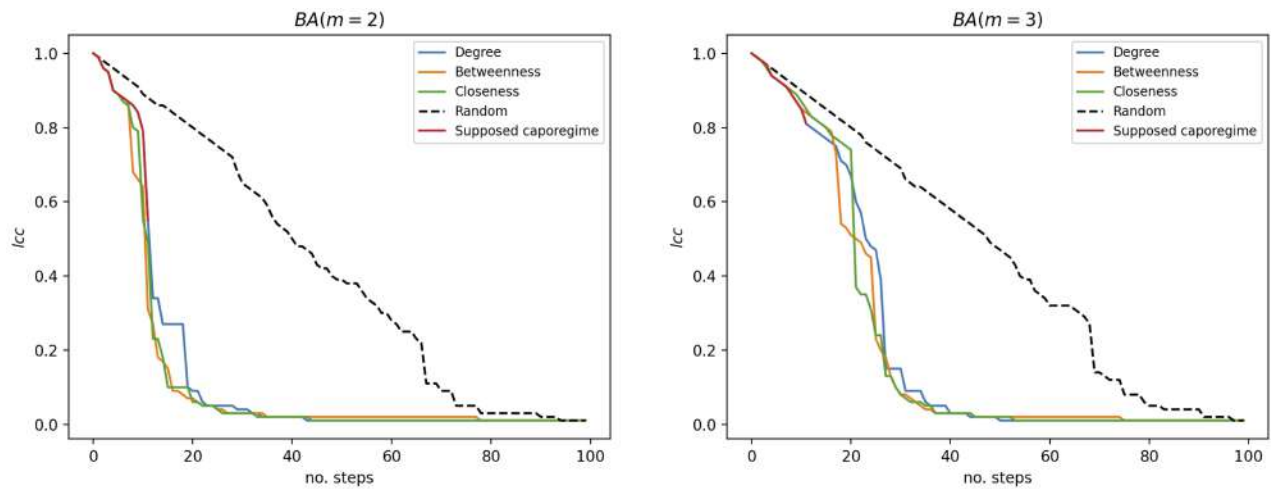


Fig. 8. Largest connected component in Barabási-Albert models.

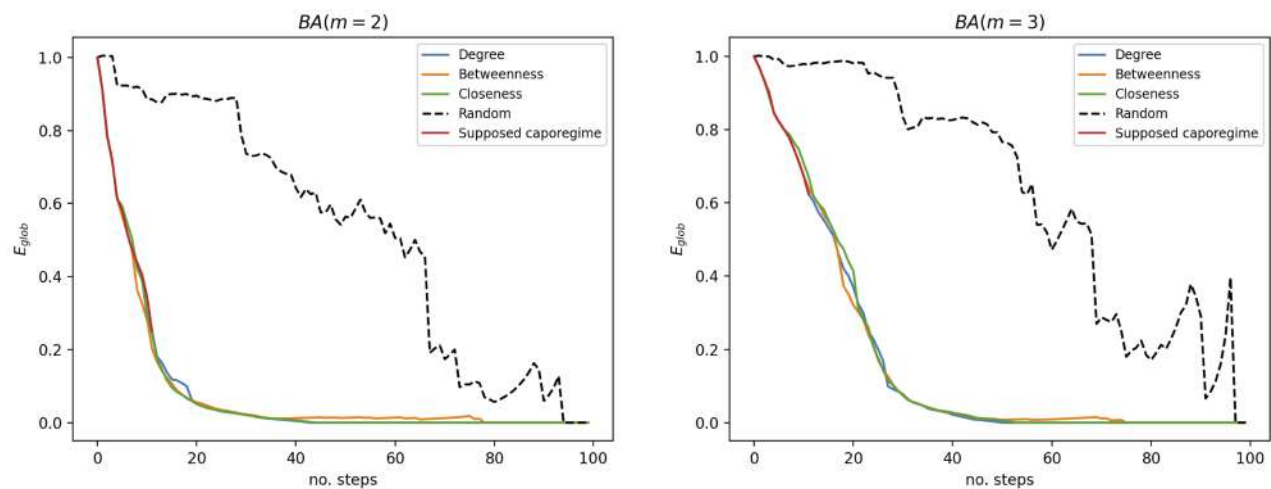


Fig. 9. Global efficiency in Barabási-Albert models.

different: for instance, most of the contacts of Pepe belonged to the Rome underworld while some of the contacts of Yakovlev had access to violence. The neighborhoods of each of the aforementioned nodes significantly differ and three distinct sub-groups of nodes emerged in the network.

A further example clarifying the limitations of centrality metrics as a tool to unveil the structure of criminal organization is due to Campana [35] who built and analyzed a network describing human trafficking between Nigeria and Italy. In such a network, node degree indicates the level of participation of an individual in trafficking activities and, thus, one would be tempted to conclude that high degree nodes are also the key players in trafficking crimes. Such a conclusion, however, is false: in fact some actors (*transporters*) were in charge of transporting victims while others (*exploiters*) were involved in exploiting them. Nodes associated with exploiters usually displayed a low degree because an exploiter does not (generally) create any link with other exploiters and each exploiter creates a link with one transporters any times it is required to do so. Therefore, a network destruction strategy targeting at high-degree nodes is ineffective because it ignores exploiters. A number of strategies can be envisaged to augment the ability of centrality metrics to discover key players in a criminal organization. Some possible strategies are as follows:

- 1) Node-level attributes (e.g., demographics, skills and so on) should be used in conjunction with centrality metrics to identify key roles in a criminal organization. Edge-level attributes (which, for instance, describe the type as well as the intensity of interactions between two actors) are also extremely useful to better understand the organization of a gang. A promising research avenue consist of applying Graph Neural Networks [43] to generate rich embeddings for nodes and edges in a criminal graph and use such embeddings for downstream tasks. Criminal organizations evolve over time and, consequently, the networks describing them change too; therefore, some centrality metrics which are effective in detecting top players at the onset of the organization are no longer effective when the organization strictly integrates with the surrounding environments (e.g. politicians and entrepreneurs).
- 2) We also plan to consider further network parameters which reflect how a node is tied to a specific group of nodes. For instance, we could classify as important nodes bridging heterogeneous social groups (e.g., individuals who connect a group of nodes corresponding to mobsters with a group of nodes formed by politicians or entrepreneurs). An opposite strategy would lead to

classify as important nodes which connect homogeneous group of nodes (for instance, nodes which connect a first group of nodes associated with mobsters of a gang with a second group of nodes corresponding to members of another gang). More formally, the theory of structural holes [44] could be applied to detect the best positioned individuals within the criminal network. A structural hole can be thought as a kind of gap in a social network between different social groups. An individual who acts as a bridge between these unconnected groups acquires a strategic position within the network because she/he is able to control how information flows across the network. Structural holes theory leads us to introduce a edge-level network feature called bridging (that is, the extent to which an edge links two disparate social groups) and a node-level network feature called brokerage (that is the ability of a node to controls bridges in a network). Betweenness centrality is a good measure of brokerage because a node with high betweenness centrality lies on many shortest paths in the network; however, such a measure alone is insufficient because we wish discriminate nodes on the basis of their ability to connect homogeneous groups of people from nodes capable of linking heterogeneous groups. As a consequence, further research work is needed to extend traditional centrality metrics to the analysis of criminal networks.

## VI. CONCLUSION

Mafia networks stand out from other types of criminal networks due to their structure. In this study we simulate different types of interventions to disrupt two real Mafia networks. They compare three law enforcement interventions targeting social capital (degree centrality, betweenness centrality, closeness centrality) and three law enforcement strategies targeting human capital. The human capital based strategies target respectively the roles of entrepreneur, soldier and caporegime. Therefore, such strategies target actors belonging to a specific role inside a Mafia family rather than actors owning specific resources or skills like in other studies on criminal networks. A seventh strategy based on random removal is used as a baseline against which to compare the performance of the other six. Such strategy is comparable with opportunistic law enforcement interventions. Overall, the most effective disruption strategies are the ones targeting actors with the highest social capital, with the betweenness centrality attack being the best performing among the three. Human capital based strategies are quite ineffective, with the one targeting caporegimes getting the best performance among the three. Targeting some categories of human capital such as soldiers and entrepreneurs is even worse than random targeting. For this reason, another analysis is carried to understand if it is possible to identify a role in a Mafia network based on the ranking of nodes. Such new analysis is designed to repeat and confirm the experiments on a Barabási-Albert model which is the network model that best reproduces Mafia networks according to an our previous study. Results show once again the effectiveness of the social capital based approaches and

the supposed caporegime based strategy with respect to the random one.

This study aims at extending a line of inquiry from the disruption of specific criminal activity (e.g. cocaine trafficking [45]) to the disruption of general organized crime group activity (e.g. mafia style organization). However, it is not so easy to identify a key role within a Mafia family that can lead to the total destruction of the network after a certain number of steps. This is due to the role adaptability inside a mafia type organization like the one we study in this paper. For example, a soldier can perform several tasks such as setting fire on someone's car or shop, threatening someone, making phone contacts. These tasks do not require specific knowledge or skills. Therefore, if a soldier is arrested, he can easily be replaced by another one. The Sicilian Mafia is in fact extremely resilient against disruption precisely for its capacity to regenerate and rearrange the top positions [25].

In our study, the dynamic and adaptability properties of criminal networks [46] are not taken into account, and this depends on the particular type of our dataset. When we built our networks, we did not have access to information about the way criminals reconstructed their communication channels following arrests. Hence, our networks are static and they miss the network reconfiguration data. However, this study could offer new opportunities to LEAs to identify and target more critical actors, specialists or even potential future replacements.

An other limitation of this kind of study is related to the data source and to the modeling used for the simulations. Although criminal data are a common source, such data are vulnerable to error for several reasons. It generally suffers from incompleteness, given the covert nature of criminal networks; incorrectness, due to human errors or deceptions; inconsistency, caused by misleading information. Moreover, gathering complete network data is an impossible task, due to the feature of a criminal network to be dynamic and due to the impossibility to establish its boundaries that are often prone to ambiguity. Finally, there is no standard method in SNA to turn data into graph. This task depends on the personal experience, theoretical and practical considerations of the analysts who have to choose which individuals and criminal activities to include in the network.

## REFERENCES

- [1] J. O. Finckenaer, "Problems of definition: What is organized crime?" *Trends Organized Crime*, vol. 8, no. 3, pp. 63–83, Mar. 2005.
- [2] D. Gambetta, *The Sicilian Mafia: The Business of Private Protection*. Cambridge, U.K.: Harvard Univ. Press, 1996.
- [3] A. Ficara et al., "Social network analysis of Sicilian Mafia interconnections," in *Complex Networks and Their Applications VIII*, H. Cherifi, S. Gaito, J. F. Mendes, E. Moro, and L. M. Rocha, Eds. Cham, Switzerland: Springer, 2020, pp. 440–450.
- [4] A. Ficara et al., "Social network analysis: The use of graph distances to compare artificial and criminal networks," *J. Smart Environments Green Comput.*, vol. 1, no. 3, pp. 159–172, 2021.
- [5] A. Ficara, G. Fiumara, P. De Meo, and S. Catanese, "Multilayer network analysis: The identification of key actors in a Sicilian Mafia operation," in *Future Access Enablers for Ubiquitous and Intelligent Infrastructures*, D. Perakovic and L. Knapcikova, Eds. Cham, Switzerland: Springer, 2021, pp. 120–134.

- [6] A. Ficara, R. Saitta, G. Fiumara, P. De Meo, and A. Liotta, "Game of Thieves and WERW-Kpath: Two novel measures of node and edge centrality for Mafia networks," in *Complex Networks XII*, A. Teixeira, D. Pacheco, M. Oliveira, H. Barbosa, B. Gonçalves, and R. Menezes, Eds. Cham, Switzerland: Springer, 2021, pp. 12–23.
- [7] A. Ficara, G. Fiumara, S. Catanese, P. De Meo, and X. Liu, "The whole is greater than the sum of the parts: A multilayer approach on criminal networks," *Future Internet*, vol. 14, no. 5, p. 123, Apr. 2022.
- [8] A. Ficara et al., "Criminal networks analysis in missing data scenarios through graph distances," *PLoS ONE*, vol. 16, no. 8, pp. 1–18, 2021.
- [9] L. Cavallaro et al., "Disrupting resilient criminal networks through data analysis: The case of Sicilian Mafia," *PLoS ONE*, vol. 15, no. 8, pp. 1–22, 2020.
- [10] F. Calderoni, S. Catanese, P. De Meo, A. Ficara, and G. Fiumara, "Robust link prediction in criminal networks: A case study of the Sicilian Mafia," *Expert Syst. Appl.*, vol. 161, Dec. 2020, Art. no. 113666.
- [11] D. Camacho, M. V. Luzón, and E. Cambria, "New research methods & algorithms in social network analysis," *Future Gener. Comput. Syst.*, vol. 114, pp. 290–293, Jan. 2021.
- [12] M. D. Lyman, *Organized Crime*, 7th ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2019.
- [13] P. A. Lupsha, *Networks vs. Networking: Analysis of an Organized Crime Group*. New York, NY, USA: Pearson, 1983.
- [14] F. A. Ianni, *Ethnic Succession in Organized Crime: Summary Report*. Washington, DC, USA: U.S. Department of Justice, Law Enforcement Assistance Administration, National Institute of Law Enforcement and Criminal Justice, 1973.
- [15] B. Keeley, *Human Capital*. Paris, France: OECD Publications and Information Centre, 2007.
- [16] C. Morselli and K. Petit, "Law-enforcement disruption of a drug importation network," *Global Crime*, vol. 8, no. 2, pp. 109–130, 2007.
- [17] P. A. C. Duijn, V. Kashirin, and P. M. A. Sloot, "The relative ineffectiveness of criminal network disruption," *Sci. Rep.*, vol. 4, no. 1, p. 4238, Feb. 2014.
- [18] S. Hashimi and M. Bouchard, "On to the next one? Using social network data to inform police target prioritization," *Policing*, vol. 40, no. 4, pp. 768–782, Nov. 2017.
- [19] B. G. Westlake, M. Bouchard, and R. Frank, "Finding the key players in online child exploitation networks," *Policy Internet*, vol. 3, no. 2, pp. 1–32, 2011.
- [20] D. M. Schwartz and T. D. A. Rouselle, "Using social network analysis to target criminal networks," *Trends Organized Crime*, vol. 12, no. 2, pp. 188–207, Jun. 2009.
- [21] M. Alzaabi, K. Taha, and T. A. Martin, "CISRI: A crime investigation system using the relative importance of information spreaders in networks depicting criminals communications," *IEEE Trans. Inf. Forensics Security*, vol. 10, no. 10, pp. 2196–2211, Oct. 2015.
- [22] K. Taha and P. D. Yoo, "SIIMCO: A forensic investigation tool for identifying the influential members of a criminal organization," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 4, pp. 811–822, Apr. 2016.
- [23] K. Taha and P. D. Yoo, "Using the spanning tree of a criminal network for identifying its leaders," *IEEE Trans. Inf. Forensics Security*, vol. 12, no. 2, pp. 445–453, Feb. 2016.
- [24] K. Taha and P. D. Yoo, "Shortlisting the influential members of criminal organizations and identifying their important communication channels," *IEEE Trans. Inf. Forensics Security*, vol. 14, no. 8, pp. 1988–1999, Aug. 2019.
- [25] A. Ficara, F. Curreri, G. Fiumara, P. De Meo, and A. Liotta, "Covert network construction, disruption, and resilience: A survey," *Mathematics*, vol. 10, no. 16, p. 2929, Aug. 2022.
- [26] V. Krebs, "Mapping networks of terrorist cells," *Connections*, vol. 24, no. 3, pp. 43–52, 2002.
- [27] M. Tsvetovat and K. Carley, "Structural knowledge and success of anti-terrorist activity: The downside of structural equivalence," *J. Social Struct.*, vol. 6, 2005. [Online]. Available: <https://www.cmu.edu/joss/content/articles/volume6/TsvetovatCarley/index.html>
- [28] T. Spapens, "Macro networks, collectives, and business processes: An integrated approach to organized crime," *Eur. J. Crime, Criminal Law Criminal Justice*, vol. 18, no. 2, pp. 185–215, 2010.
- [29] H. Nguyen and M. Bouchard, "Need, connections, or competence? Criminal achievement among adolescent offenders," *Justice Quart.*, vol. 30, no. 1, pp. 44–83, Feb. 2013.
- [30] P. A. C. Duijn and P. P. H. M. Klerks, *Social Network Analysis Applied to Criminal Networks: Recent Developments in Dutch Law Enforcement*. Cham, Switzerland: Springer, 2014, pp. 121–159.
- [31] D. Bright, C. Greenhill, T. Britz, A. Ritter, and C. Morselli, "Criminal network vulnerabilities and adaptations," *Global Crime*, vol. 18, no. 4, pp. 424–441, Oct. 2017.
- [32] S. Villani, M. Mosca, and M. Castiello, "A virtuous combination of structural and skill analysis to defeat organized crime," *Socio-Econ. Planning Sci.*, vol. 65, pp. 51–65, Mar. 2019.
- [33] P. Campana and F. Varese, "Studying organized crime networks: Data sources, boundaries and the limits of structural measures," *Social Netw.*, vol. 69, pp. 149–159, May 2022.
- [34] F. Varese, "The structure and the content of criminal connections: The Russian Mafia in Italy," *Eur. Sociol. Rev.*, vol. 29, no. 5, pp. 899–909, Oct. 2013.
- [35] P. Campana, "The structure of human trafficking: Lifting the bonnet on a Nigerian transnational network," *Brit. J. Criminol.*, vol. 56, no. 1, pp. 68–86, Jan. 2016.
- [36] P. Erdős and A. Rényi, "On random graphs I," *Publicationes Mathematicae*, vol. 6, pp. 290–297, Jan. 1959.
- [37] D. J. Watts and S. H. Strogatz, "Collective dynamics of small-world networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998.
- [38] A.-L. Barabási and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, no. 5439, pp. 509–512, Oct. 1999.
- [39] L. Cavallaro et al., "Criminal network: The Sicilian Mafia," in *Montagna Operation*. Geneva, Switzerland: CERN, 2020.
- [40] L. C. Freeman, "Centrality in social networks conceptual clarification," *Social Netw.*, vol. 1, no. 3, pp. 215–239, 1979.
- [41] U. Brandes, "On variants of shortest-path betweenness centrality and their generic computation," *Social Netw.*, vol. 30, no. 2, pp. 136–145, May 2008.
- [42] V. Latora and M. Marchiori, "Efficient behavior of small-world networks," *Phys. Rev. Lett.*, vol. 87, Oct. 2001, Art. no. 198701.
- [43] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A comprehensive survey on graph neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 1, pp. 4–24, Jan. 2020.
- [44] R. Burt, "Structural holes," in *Social Stratification*. Evanston, IL, USA: Routledge, 2018, pp. 659–663.
- [45] A. Aziani, G. Berlusconi, and L. Giommoni, "A quantitative application of enterprise and social embeddedness theories to the transnational trafficking of cocaine in Europe," *Deviant Behav.*, vol. 42, no. 2, pp. 245–267, Feb. 2021.
- [46] G. Berlusconi, "Come at the king, you best not miss: Criminal network adaptation after law enforcement targeting of key players," *Global Crime*, vol. 23, no. 1, pp. 44–64, Jan. 2022.

**Annamaria Ficara** received the Ph.D. degree in mathematics and computational sciences from the University of Palermo, Italy. She has been an Assistant Professor with the University of Pisa, Italy. She is currently an Assistant Professor of computer science with the University of Messina, Italy. Her main research interests include network science, social network analysis, criminal networks, and complex systems.

**Francesco Curreri** received the Ph.D. degree in mathematics and computational sciences from the University of Palermo, Italy. His main research interests include system identification and nonlinear systems modeling, soft sensors, neural models, social network analysis, and criminal networks.

**Giacomo Fiumara** (Member, IEEE) received the Ph.D. degree in physics in 1993. He has been an Associate Professor of computer science with the University of Messina, Italy, since 2009. He has published more than 80 papers in international journals and conference proceedings. His research interests include network science, criminal networks, and simulations of model systems. He is a member of various conference PCs.

**Pasquale De Meo** received the Ph.D. degree in systems engineering and computer science from the University of Calabria. He has been a Marie Curie Fellow with Vrije Universiteit Amsterdam. He is currently an Associate Professor of computer science with the Department of Ancient and Modern Civilizations, University of Messina, Italy. His main research interests include social networks, recommender systems, and user profiling.