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Disrupting Criminal Networks: A Study of Social and Human Capital Strategies

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Abstract: Social Network Analysis (SNA) is a multidisciplinary field dedicated to uncovering patterns within interpersonal interactions. Within this framework, SNA has been utilized extensively to elucidate the structures of criminal networks, identifying key players, subgroups, and vulnerabilities. This paper explores the efficacy of seven disruption strategies applied to real Mafia networks using SNA methodologies. Three interventions focus on actors possessing significant social capital, while three target those with substantial human capital. These strategies are compared to each other and random node removal, shedding light on their relative effectiveness in disrupting criminal networks.

***Index Terms* - Criminal networks, Social Network Analysis, Disruption, Social capital, Human capital, Random.**

I. INTRODUCTION

Criminal 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. Because of their strong resilience to disruption, such networks pose tough challenges to Law Enforcement Agencies (LEAs). Herein, we use 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, identify subgroups highlight actors in strategic positions, and develop disruption and prevention methods [1], [2].

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 individual's attributes and resources 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" [3].

II. LITERATURE REVIEW

F. Calderoni, S. Catanese, P. De Meo, A. Ficara, and G. Fiumara, [1], proposed issues by assessing the performance of different link prediction algorithms on a mafia organization. The analysis relies on an original dataset manually extracted from the judicial documents of operation "Montagna", conducted by the Italian law enforcement agencies against individuals affiliated with the Sicilian Mafia.

Ficara et al [2], proposed a theory to study social phenomena, which was found to be highly relevant in areas like Criminology. This paper provides an overview of key methods and tools that may be used for the analysis of criminal networks, which are presented in a real-world case study and extracted data on the interactions among suspects within two Sicilian Mafia clans, obtaining two weighted undirected graphs.

B. Keeley [3], proposed the increasing economic and social importance of human capital--our education, skills, competencies, and knowledge. Raising human capital has emerged as a key policy priority, particularly for low-skilled individuals, who are at risk of being left even further behind. Policy in this area focuses on early childhood development, improving quality and choice in schooling, creating excellence in tertiary education, and widening access to adult learning.

L. Cavallaro et al. [4], proposed methods and tools from Social Network Analysis (SNA) to (i) unveil the structure and organization of Sicilian Mafia gangs, based on two real-world datasets, and (ii) gain insights as to how to efficiently reduce the Largest Connected Component (LCC) of two networks derived from them. Our analysis simulated different intervention procedures: (i) arresting one criminal at a time (sequential node removal), and (ii) police raids (node block removal). In both the sequential and the node block removal intervention procedures, the Betweenness centrality was the most effective strategy in prioritizing the nodes to be removed.

L. Cavallaro et al [5], proposed The Sicilian Mafia is a highly interconnected network with a strong core. The core of the network is composed of the most important Mafiosi, who are responsible for coordinating the activities of the network. The authors use a variety of network analysis techniques to analyze the structure of the Mafia network. The authors find that the Mafia network is very similar to other criminal networks, such as drug trafficking networks. The paper by Cavallaro et al. is a valuable resource for anyone who wants to learn more about the Sicilian Mafia. The author's findings can be used to develop strategies for combating the Mafia and to prevent future criminal activity.

L. C. Freeman [6], proposed that with the development of the economy today, Bank business is deeply integrated into our lives. Thousands of transactions generate large amounts of data. Traditional bank customer management system simply classifies and count these data, and the system is deficient in customer relationship management. However, the social network model can provide the influence between the bank customers for the bank. Constructed a social network by calculating the relationship between bank customers.

U. Brandes [7], proposed Betweenness centrality based on shortest paths is a standard measure of control utilized in numerous studies and implemented in all relevant software tools for network analysis. The calculation of the weight of the value of the node uses betweenness centrality, where the value of the node is determined by how much the other two nodes pass the i th node in the graph based on the shortest distance. The edge weights greatly influence the shortest paths calculated using the graph. Edge ranking based on this criterion is called edge betweenness centrality.

P. A. C. Duijn, V. Kashirin, and P. M. A. Sloot [8] investigated the impact of the targeting of key players by law enforcement on the structure, communication strategies, and activities of a drug trafficking network. Data are extracted from judicial court documents. This paper combines a quantitative element where network statistics and exponential random graph models are used to describe and explain structural changes over time, and a qualitative element where the content of wiretapped conversations is analyzed.

A. Ficara, F. Curreri, G. Fiumara, P. De Meo, and A. Liotta [9], delves into the intricate realm of criminal networks, with a specific focus on Mafia organizations, through the lens of Social Network Analysis (SNA). The primary aim of this research is to gain a deep and comprehensive understanding of the structure and dynamics of covert criminal networks and to develop effective strategies for disrupting and combatting organized crime. This study tested the determinants of drug trafficking through crypto markets by using a mix of social network analysis and a new dataset composed of self-reported transactions

G. Berlusconi [10], investigated the impact of the targeting of key players by law enforcement on the structure, communication strategies, and activities of a drug trafficking network. Data are extracted from judicial court documents. This paper combines a quantitative element where network statistics and exponential random graph models are used to describe and explain structural changes over time and a qualitative element where the content of wiretapped conversations is analyzed. This paper contributes to the growing literature on the efficiency security trade-off in criminal networks and discusses policy implications for repressive policies in illegal drug markets.

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III. CRIMINAL NETWORK DATASET

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

Link to the Datasets: Dataset

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

Table 1. List of Attributes and the number of nodes who possess each in Meetings and Phone Calls extracted from Montagna Operation.

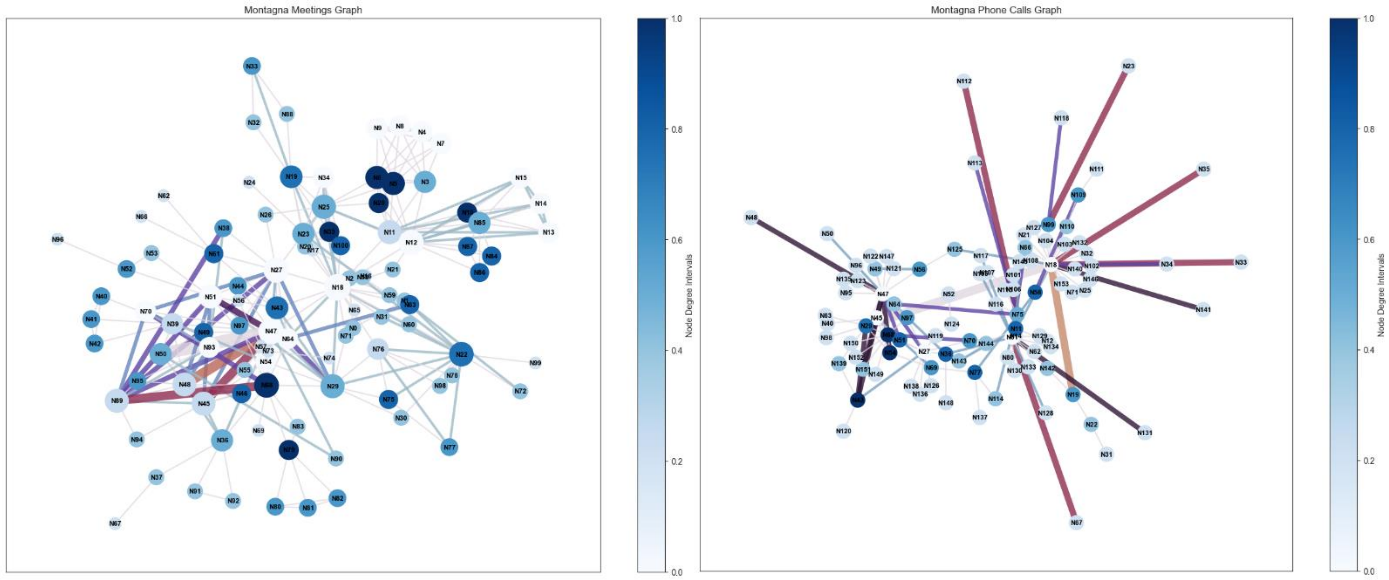

Fig 1. The Montagna Meetings M_M and Phone Calls M_{PC} networks. The edge width is equal to the edge weights, i.e., the number of meetings or phone calls. The node size is proportional to the node degree.

IV. CRIMINAL NETWORK DISRUPTION STRATEGIES

Each of these interventions is modeled by a targeting method that 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 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

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^0_{glob} 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;
  $E^s_{glob} = E^s_{glob}/E^0_{glob}$;
end

The social capital disruption approach aims at strategic positions within criminal networks. Three main strategies have been used: degree centrality attack, betweenness centrality attack, and closeness centrality attack.

Degree centrality (DC) [6] 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.

Betweenness centrality (BC) [7] measures how frequently a node lies on the shortest paths between other pairs of nodes:

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

where v^i_{hk} is the number of shortest paths from actor h to actor k by passing through i and g_{hk} is the total number of shortest paths from h to k.

Closeness centrality attacks are implemented by removing the actors sequentially according to the maximal closeness centrality. Closeness centrality (CL) [6] 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.

B. Random Disruption

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^0_{glob} 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;
  $E^s_{glob} = E^s_{glob} / E^0_{glob}$;
end

The random disruption approach follows no preference or ranking during the actor selection for removal. 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 [8].

C. Human Capital Disruption

Algorithm 3 Human Capital Disruption

% Initialization;
set an undirected graph $G = (V, E)$;
add customize 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^0_{glob} 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;
  $E^s_{glob} = E^s_{glob} / E^0_{glob}$;
end

The human capital disruption strategy consists of targeting actors with specific roles in a Mafia family. 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, soldiers, and caporegimes attacks are implemented by removing the actors with the specific roles of entrepreneur, soldier, and caporegime in order of decreasing DC.

V. RESULTS

Our results show that the social capital approach can 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.

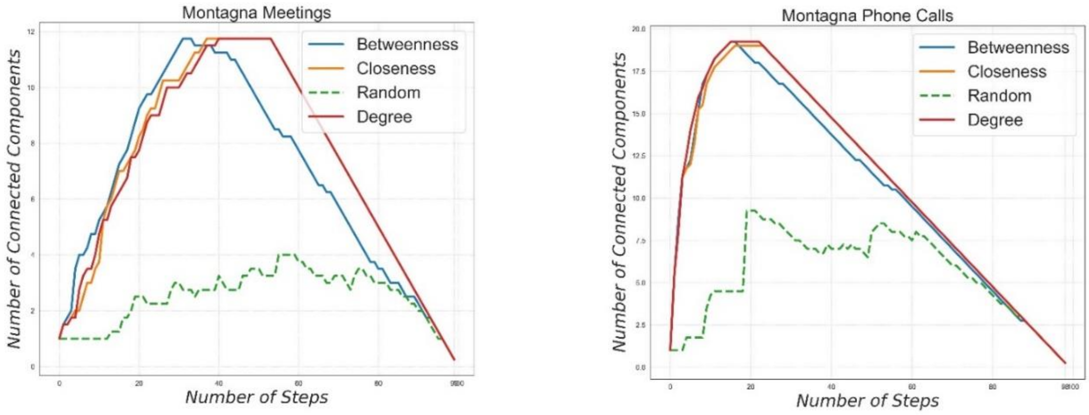

Fig 2. Number of Connected Components in Montagna Meetings and Phone Calls

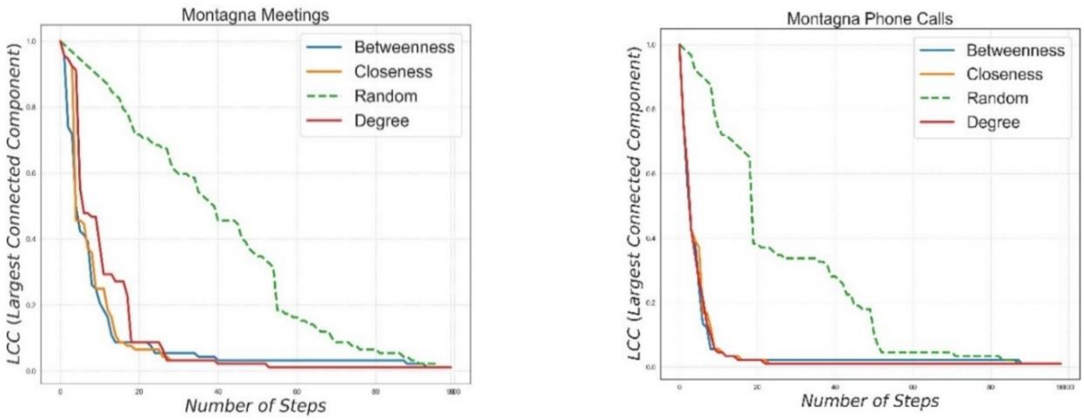

Fig 3. Largest Connected Component in Montagna Meetings and Phone Calls

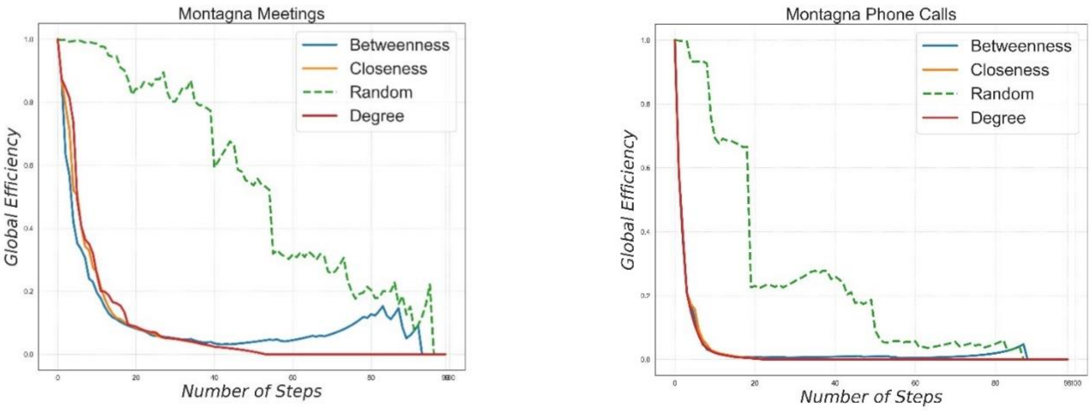

Fig 4. Global Efficiency in Montagna Meetings and Phone Calls

Based on this good result about the removal of the highest centrality node, we decided to rank nodes according to their degree of connectivity, highlighted in blue. The nodes with the same rank are the nodes with the same centrality measure in both M_M and M_{PC} networks.

The human capital approach is as ineffective as the random one or even worse when soldiers or entrepreneurs are removed. Then, we did a different kind of analysis to know:

1) If it is possible to identify the 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.

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 able to disrupt the networks as the degree, betweenness, and closeness targeting.

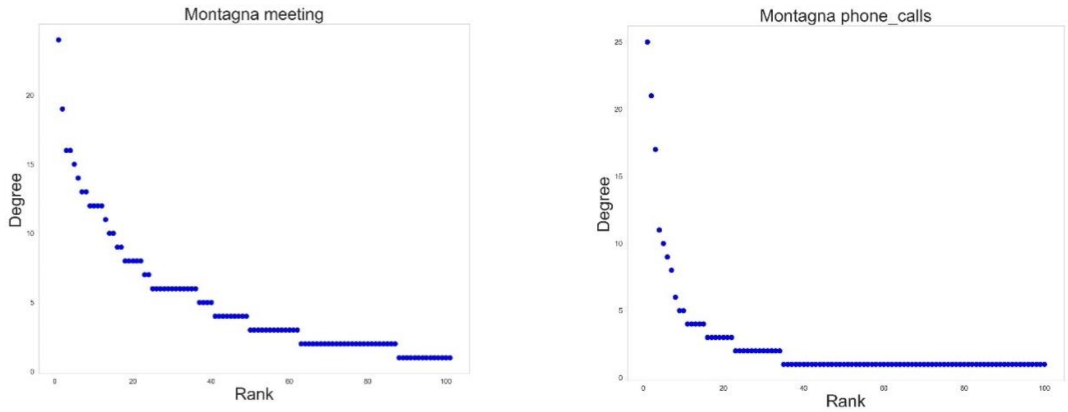

Fig 5. Ranking nodes in Montagna Meetings and Phone Calls

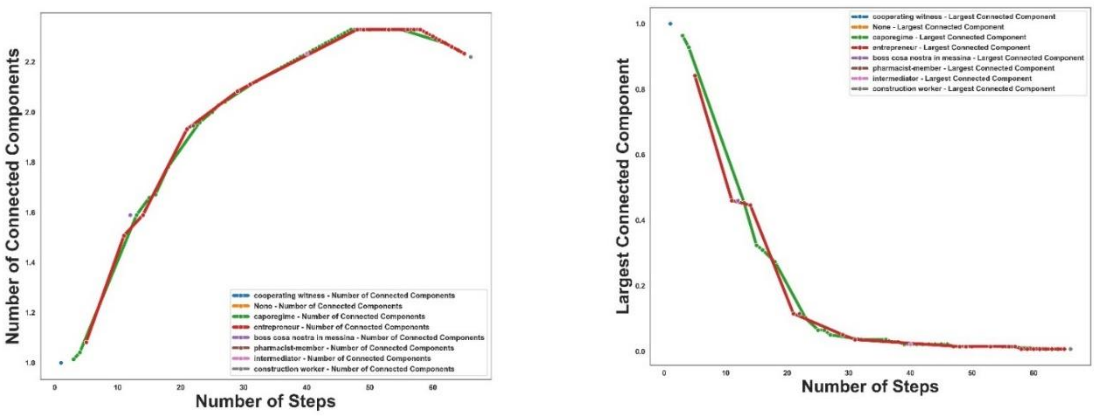

Fig 6. Number of Connected Components and Largest Connected Component in Montagna Roles

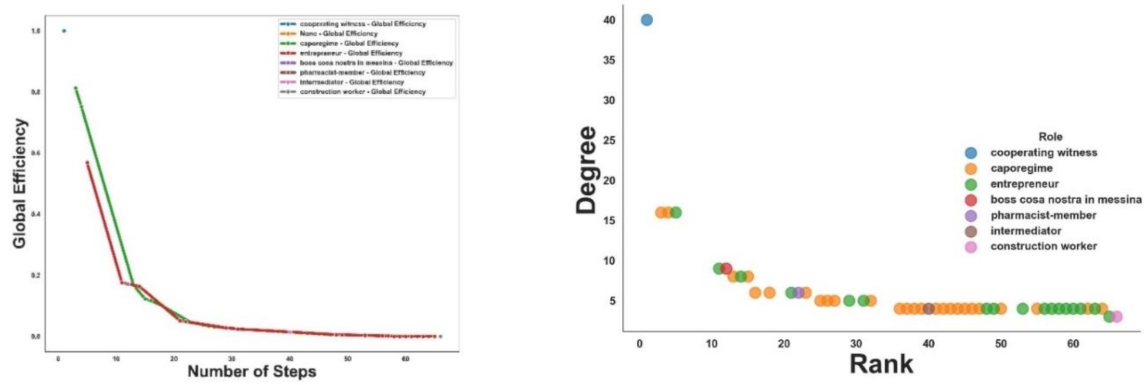

Fig 7. Global Efficiency and Ranking Nodes in Montagna Roles

Based on this good result about the removal of caporegimes, we decided to rank nodes according to their degree of connectivity, highlighting in yellow the caporegimes. Highlighted in yellow are the nodes with the same rank as the caporegimes in both M_M and M_{PC} networks i.e., the supposed caporegimes.

VI. CONCLUSION

Mafia networks possess distinctive structural characteristics that set them apart from other criminal networks. In this study, we conducted simulations to assess various intervention strategies aimed at disrupting two authentic Mafia networks. Our analysis compares three law enforcement interventions targeting social capital (degree centrality, betweenness centrality, closeness centrality) with three strategies targeting human capital. These human capital-based strategies specifically focus on disrupting the roles of entrepreneur, soldier, and caporegime within Mafia families. For example, a soldier can perform several tasks such as setting fire to someone's car or shop, threatening someone, and 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 extremely resilient against disruption precisely because of its capacity to regenerate and rearrange the top positions [9]. 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 [10]. Unlike previous studies on criminal networks that target actors based on specific resources or skills, our approach targets actors based on their roles within the Mafia hierarchy. This nuanced strategy offers valuable insights into disrupting the intricate dynamics of Mafia networks and highlights the importance of understanding and targeting specific roles within criminal organizations.

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