Longitudinal Analysis of the Topology of Criminal Networks using a Simple Cost-Benefit Agent-Based Model

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Abstract. Recently, efforts have been made in computational criminology to study the dynamics of criminal organisations and improve law enforcement measures. To understand the evolution of a criminal network, current literature uses social network analysis and agent-based modelling as research tools. However, these studies only explain the short-term adaptation of a criminal network with a simplified mechanism for introducing new actors. Moreover, most studies do not consider the spatial factor, i.e. the underlying social network of a criminal network and the social environment in which it is active. This paper presents a computational modelling approach to address this literature gap by combining an agent-based model with an explicit social network to simulate the long-term evolution of a criminal organisation. To analyse the dynamics of a criminal organisation in a population, different social networks were modelled. A comparison of the evolution between the different networks was carried out, including a topological analysis (secrecy, flow of information and size of largest component). This paper demonstrates that the underlying structure of the network does make a difference in its development. In particular, with a preferentially structured population, the prevalence of criminal behaviour is very pronounced. Moreover, the preferential structure provides criminal organisations a certain efficiency in terms of secrecy and flow of information.

Keywords: criminal networks · agent-based modelling · social network analysis · social opportunity

1 Introduction

To adequately respond to a persistent and rampant issue of illicit activities, such as human trafficking and drug production [26,27], the latest advancements in mathematics and computational power are used as a decision-driven tool to increase the effectiveness of the intervention methods against organised crime [11,12,14]. The objective of this research was to explore and analyse the possible evolution of any criminal network through an agent-based model while addressing the gap in the literature. Based on the data provided by the intelligence

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services or constructed from publicly available data, a network can be reconstructed upon which a social network analysis is applied to determine its characteristics and define the key players[3] [1,4,6,9,10,11,12,34]. Given the covert nature of criminal networks and the difficulty of updating information about them, current literature is often forced to base its research on static portrayals of criminal ties[4] [11,30]. However, criminal organisations have been found to have a fluid structure where re-structuring is a constant process to adapt to endogenous and exogenous factors such as gang rivalries or police interventions [35]. Thus, the resilience of a network is defined by how well the organisation can mitigate damage and maintain its illegal activity. It has been found that interventions can have unintended effects in the long term, such as becoming relatively ineffective or forcing the dispersion of criminal activities across an area [12,17,24]. To increase the efficiency of dismantling interventions, it is imperative to understand the dynamic of the criminal organisation (CO) and the possible repercussions an intervention can have. As noted earlier, most studies focus on static networks and attempt to provide information about their characteristics when interventions are simulated. Yet, static snapshots of criminal networks contain only partial information and thus longitudinal data is preferred[5]. To tackle the lack of longitudinal data about criminal networks and provide insights into the criminal network resilience behaviour, various approaches have been adopted.

On the one hand, there is a large volume of published studies describing the evolution of a criminal network after introducing a fictitious police intervention [4,12,14]. In a study investigating the dynamics of a CO, Behzadan et al. [4] simulated the evolution of a CO from a game-theoretic perspective. To mimic the dynamics, information about the actors is needed, such as: their nationality, languages spoken, or function within the organisation. However, most data sets do not contain an exhaustive list of variables. Duxbury and Haynie [14] performed a similar study, using a combination of agent-based modelling with social network analysis to provide some insights into the mechanism behind the resilience by introducing the concept of trustworthiness: a liaison between actors also depends on trust. Distinguishing between profit-oriented and security-oriented networks,

[3] In this context, key players are regarded as important actors who ensure the proper functioning of the organisation. In their absence, the organisation would break into considerably smaller fragments leading to a reduction in productive capacity

[4] A static criminal network is defined as a network whose links between nodes are assumed to be unchanged. Thereby, in social network analysis, nodes (vertices) correspond to actors and links (edges) to relations. The term "relation" depends on the context of the data in question. It can represent a simple acquaintance between two persons, defined by work relation, friendship, kingship or membership of the association [9], or it can also represent a medium by which resources are shared between actors [33]. Moreover, a network can be shaped by various types of ties, including strong ties which denote close and trusted connections, weak ties which refer to more distant and casual connections with lower intimacy and less frequent interaction, and latent ties which represent potential connections that are not actively utilised [13].

[5] The term longitudinal refers to the succession of consecutive snap-shots of the criminal networks over a certain period, resulting in a time-varying network.

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the formation of new ties will depend on the CO's motive. In security-oriented networks, the flow of information is restricted, thus liaisons between actors with low degree centrality are more likely to be created. In a profit-oriented network, a high interconnection between actors is the driving force of the simulated dynamic. However, the models in [4,14] assume rational behaviour of the actors and perfect knowledge of the network; the actors know each other's attributes. In contrast, access to information in a security-oriented organisation — such as the terrorist network studied in the aforementioned article — is severely restricted so as not to jeopardise its activities [6,14]. Duijn et al. [12] analysed the evolution of a CO by introducing the economical concept of the human capital approach; new liaisons are created between actors holding either a similar role or interrelated roles. Calderoni et al. [9] tackled the question of the dynamics of a criminal network from a recruitment point of view using various policies as an exogenous factor. Amongst the policies tested, insights into the influence of family members belonging to the mafia and the influence of social support to families at risk were highlighted. One of the limitations of the model is that the research was applied to a case study, which does not necessarily have a broader application. Furthermore, the impact of imprisonment on an agent's decision to re-enter the organisation is neglected. Having access to a longitudinal criminal network, some studies compared various mechanisms such as preferential attachment, triadic closure, or role-similarity to assess their goodness of fit of the simulated dynamics [6,7]. However, the authors faced the challenge of missing data. These simulations explain the short-term adaptation of a criminal network. After an intervention, most COs are able to fill the role of the neutralised criminal and resume their activity after a few days to weeks [19,24]. Additionally, the emergence of new actors is either not explained or not taken into account in these models. On the other hand, there are publications that concentrate on adopting a game-theoretical approach to model the evolution of criminal behaviour within a population [5,18,21]. Martinez-Vaquero et al. [18] and Perc et al. [21] attempted to show a more general analysis of the emergence of criminal behaviour by considering the effect of policies, such as jurisdiction penalty, social exclusion, and clerical self-justice. During the simulation, actors decide to act either as honest citizens or criminals and collect the respective remuneration, referred to as fitness points. The policies act as control variables influencing the presence of the different roles within the population. Berenji et al. [5] further add to the policy-focused model approach by tackling the line of inquiry by introducing the aspect of rehabilitation. Despite the promising results, these studies do not account for the possible influence of a network-like structure on the model. It is believed that when studying the spread of criminal behaviour within a population, it is important to consider its underlying social ties. Based on the aforementioned studies, a literature gap can be asserted concerning the publications focusing on short-term evolutions of a CO [4,9,12,14] and those focusing on long-term developments of criminal behaviour in a population but neglecting the influence of a social network structure in their simulations [18,21].

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To bridge the identified literature gap, this paper aims at formulating a model that simulates the long-term evolution of a CO by combining a developed recruitment mechanism with network-explicit configurations. As noted in [9,18], it is believed that understanding the recruitment mechanism of a CO will add to the longevity of the dynamic evolution and give an adequate answer to how new actors emerge in a CO. This is achieved by using a different adaptation of Martinez-Vaquero et al. [18]'s model, where social ties are taken into account: this is the network-explicit configuration that is modelled in this paper. By developing this model, using the network-explicit configuration, the research will provide (i) social relevance insofar as it could further aid the understanding of criminal network growth, and (ii) practical relevance in that it could further the ability of authorities to predict this evolution and develop appropriate interventions.

2 Methodology

2.1 Agent-based modelling

The following agent-based model is extended based on the conceptual framework proposed by [18]. As stated by Martinez-Vaquero et al. [18], to model the growth or decline of a criminal network it is important to define the conditions leading a person to join such an organisation. Consequently, that is most adequately done using three different types of agents: honest, member of a criminal organisation (MCO), and lone actors. The lone actors are deemed important since they account for cases where one does not join an organisation but prefers to act independently. Through a cost-benefit game, the entities interact with each other and decide to adopt the best strategy, which involves either becoming honest, or MCO, or a lone actor. The driving force of the model is a punishment/reward system which influences the decision-making of the agents. For honest citizens, MCOs and lone actors, the reward reflects the success of their activities. Based on the theory of social opportunity, an agent's success can influence his/her entourage to imitate him/her [12,18]. The punishment system is exerted through the introduction of three meta-agents: the criminal court of justice, social control, and the pressure exerted by a CO. The meta-agents do not correspond to a specific node but merely represent an abstract agent which oversees the game. The mechanism of the agent-based model, including the acting, investigation and evolutionary stage is based on the original paper [18]. For the purpose of conciseness, the reader is directed to consult the original paper for further details. The distinction between this model and the original lies in the fact that the interactions between agents are governed by an underlying network. Thus, the groups, as defined in the original literature, are composed of the selected player and all its immediate neighbours who share a connection. As a result, the computation of reward and damage points can be carried out directly, rather than using the mean-filed approach. The following pseudo-code gives an overview of the agentbased model's (ABM) mechanism. Alternatively, a more detailed explanation including the ODD+ protocol can be studied. The definition and default values of the parameters are indicated in Table 1. The table serves merely as

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a reference point for subsequent analysis in which one or more parameters are subject to changes. The default combinations of parameters have been chosen

Algorithm 1: Modified Agent-based model based on Martinez-Vaquero et al.

```
input  : A network with nodes having a fitness and status attribute
output: The evolution of status of the population and the topological change of the criminal network
for i ← 1 to n_rounds do
    victimiser = select_random_person(network); // select random victimiser
    // Acting stage
    if victimiser.status == criminal then
        inflict_damage(neighbours,c_c); // inflict damage to all non-MCO neighbours
        victimiser.fitness +(r_c × c_c)/n_c;
        criminal_neighbours.fitness+(r_c × c_c)/n_c // all the MCO neighbours get the same benefit
    else if victimiser.status == wolf then
        if U(0,1) ≥ 1 − δ(1 − n_c) then
            inflict_damage(neighbours,c_w); // inflict damage to all the neighbours
            victimiser.fitness +(c_w × r_w);
            criminal_neighbour.fitness+τ(r_w × c_w)/n_c
    // Investigation stage
    // Investigation is successful if victimiser has been found
    // If select_random_person(network) == victimiser
    if state_investigation == successful then
        victimiser.fitness -β_s;
    if honest_investigation == successful then
        victimiser.fitness -(β_h × n_h);
    if criminal_investigation == successful AND victimiser.status == wolf then
        victimiser.fitness -(β_c × n_c);
    if honest_investigation/state_investigation == successful AND victimiser.status ==criminal then
        // All the criminal neighbours get also a penalty
        // If an investigation stage is unsuccessful, the respective term (β_s/β_h)is 0
        criminal_neighbours.fitness -γ × (β_s + β_h × n_h);
    // Evolutionary stage
    random_person == select_random_person(network);
    if U(0,1) ≤ mutation_prob then
        random_person.status = random_select(["c","h","w"]); // randomly switch stage
    else
        fermi_function(random_person,random_neighbour); // adopt random_neighbour status based
            on Fermi function
```

such that the reward points are the same for MCOs and lone actors, and the penalty systems are equal. Furthermore, the influence of the CO on lone actors as well as the penalty share between MCOs was set to a relatively low value.

2.2 Network Initialisation

To introduce a network-explicit agent-based model, [18]'s model has been built upon by firstly taking an initial criminal network as defined in the literature, and constructing it with the inclusion of "honest" and "lone actors" nodes using different attachment methods. The attachments are: random, preferential, and small-world. These attachment methods have helped explain various networks observed in nature [3,15,31]. The preferential attachment has proven to be interesting, especially as it can explain the properties of social networks such as

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Table 1. Overview of the parameters used for the Agent-based model. The reward, damage, and punishment parameters are based on [18].

Parameters	Default value	Explanation
δ	0.7	Influence factor of an independent actor to act
τ	0.1	Influence factor of an independent actor's action on CO
γ	0.1	Punishment sharing factor for members of a CO
β_s	1	State punishment value
β_h	1	Civil punishment value
β_c	1	Criminal punishment value
c_w	1	Damage caused by a lone actor
c_c	1	Damage caused by a member of a CO
r_w	1	Reward factor for a lone actor
r_c	1	Reward factor for a member of a CO
T	10	Temperature factor for the Fermi function
$mutation_{prob}$	0.0001	Probability of undergoing random mutation

the scale-free property [2]. The random network, also called Erdos-Rényi network, accounts for the small-world theory where any two persons are separated by a chain of social acquaintances of a maximum length of six. In contrast, the small-world network, also referred to as the Watts-Strogatz network, generates a random network which can predict a precise clustering coefficient and average path length [2]. In other words, honest citizens and lone actors have been added to a criminal network using the different attachment methods. Thereby, the initial links amongst the criminal network were not modified. The intention was to preserve the structure and thus the properties of a criminal network. The attachment methods were based on the pseudo-algorithm presented in [22] which are stochastic. Visualisation of the attachment methods can be accessed by this link. Thus the rationale behind using these different attachment methods is to provide different simulations and analyse how the configuration of ties will influence the outcome of the model. For all the attachment methods, the ratio of honest, lone actors, and MCOs were set based on the data collected by the United Nations Office on Drugs and Crime [25] concerning the average ratio of incarceration within a population. Obtaining accurate data on the number of criminals within a population is challenging due to, among others, underreporting and a lack of standardised reporting across law enforcement agencies and jurisdictions. Therefore, for simplicity, it was assumed that the number of convicts reflects approximately the number of criminals within a population. For this thesis, data on the United States was used, where approximately 1%[6] of the population is unlawful [28]. Yet, it was not possible to define out of those unlawful individuals within the population how many are part of a CO. Nevertheless, the triangular phase diagrams presented in [18] indicate that the ratio between

[6] The United Nations Office on Drugs and Crime (UNODC) presents the data as persons per 100,000 population, taking into account the entire demographic population. Thus, the interest is in the active population, defined as persons aged 18-65 years, who make up 60% of the population according to the U.S. Census Bureau. Thus on average 600 out of 100000 are incarcerated in the U.S.A., which reduced to the active population, gives 600/(0.6*100000)=1%.

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lone actors and MCOs does not impact the convergence to the same equilibrium, merely that the convergence rate is expected to be subject to changes.

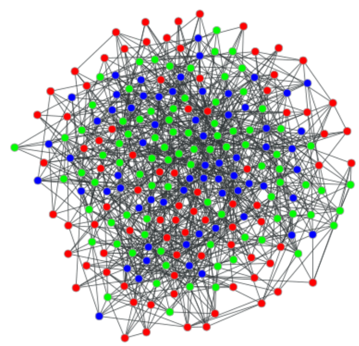

Fig. 1. Visualisation of the population created with the small-world algorithm, including criminals (red), lone actors (blue) and honest citizens (green).

To achieve a fair comparison of the results between the populations of different structures (preferential/random/small-world), it was important that they had common characteristics (see Table 2). It was decided that the different structures should have the same density δ which corresponds to having approximately the same amount of nodes and edges. This density was set to the one observed in the initial criminal network[7]. To make sure that the small-world network does not become a random network by setting the rewiring probability *prob* too high, the proximity-ratio test was performed [29]. Furthermore, the average clustering coefficient is higher in small-world networks than in random networks despite having similar average path length, which confirms the literature [22].

2.3 Determine Topological Changes

The focus of this research is on the development of the criminal network within the population. As a result, only the nodes with a criminal state were retained for the topological measurements. Throughout each round, some measures were collected, which gives an indication of the structure of the network and how it evolves. The measurements include some standard metrics, such as the size of the largest components, the flow of information, and the density of the network [10,11,14,34]. [11] defined the size of the largest component as a measure of interest, based on the reasoning that it represents a "self-organised criminal

[7] The density has been chosen to be the same as the initial criminal network in order to avoid forcing the criminal network to evolve into a less dense network. By doing so, the criminal network has the option to either keep the same density or evolve towards a less dense configuration.

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Table 2. Overview of the properties of the different population structures. *prob* corresponds to the probability of rewiring an existing link. δ corresponds to the density. $\langle k \rangle$ corresponds to the average degree of a node. $\langle p \rangle$ corresponds to the average degree path length. $\pm$ values represent the standard deviation for continuous distributions, respective for discrete distributions.

	Preferential	Random	Small-world
percentage of honests	99%	99%	99%
percentage of actors	0.1%	0.1%	0.1%
percentage of MCOs	0.9%	0.9%	0.9%
prob	–	–	0.2
nodes	10555 ±0	10555 ±0	10555 ±0
edges	1.50e6 ±1066	1.54e6 ±260	1.50e6 ±200
δ	0.027 ±2e-05	0.028 ±4e-06	0.027 ±3e-06
clustering coefficient	0.05 ±8e-04	0.01 ±4e-05	0.4 ±1e-04
$\langle k \rangle$	285 ±0.2	291 ±0.05	283 ±0.04
$\langle p \rangle$	2.08 ±3e-03	2.12 ±1e-04	2.47 ±1e-03
# of components	1 ±0	1 ±0	1 ±0

phase", a threat to national security. The flow of information defines how well the exchange of information and goods circulates within the largest component G and is defined by the following equation within the largest component G [11,12]:

$$\eta(G) = \frac{1}{N(N-1)} \sum_{i<j \in G} \frac{1}{d_{ij}} \tag{1}$$

where N is the total number of nodes in G and d_{ij} is the distance between node i and j. The aim is to reduce the communication flow of a network, which will lead to a decrease in its efficiency. As a result, the CO will become less successful and less attractive to be a part of. Additionally, Duijn et al. [12] formulated the secrecy metric:

$$Secrecy(G) = \frac{N(N-1)}{2E} \tag{2}$$

where E is the number of edges and N is the number of nodes in the largest component G. This corresponds to the inverse of the density metric, which expresses the ratio of actual relations over the number of possible relations. Thus, the metric indicates how exposed the network is. In other words, the more connections there are in a network, the more direct neighbours are possibly exposed by an actor questioned by the police. The difference between Equation 1 and Equation 2 is that the efficiency metric η captures the underlying structure of the network, while the secrecy metric does not take into account how the nodes are connected.

2.4 Data

For this research, the data from Cavallaro et al. [10] was selected. These data represents the social network of the Mistretta family and the Batanesi clan, a sub-branch of the Sicilian Mafia mainly involved in a cartel of construction companies. The Sicilian Mafia is described as a reactive organisation that efficiently

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adapts to external stimuli to pursue its economic and social goals. In this paper we have used the data corresponding to the recorded phone calls to construct the network used in our simulation model. The characteristics of the resulting network (Table 3) do not show anything exceptional or peculiar.

Table 3. Overview of the criminal network. N corresponds to the number of nodes, E corresponds to the number of edges, D corresponds to the diameter, $\langle k \rangle$ corresponds to the average degree, δ corresponds to the density, η corresponds to the flow of information in the network [11,12].

Montagna Phone Calls			
N = 95	E = 120	$\langle k \rangle = 2.526$	giant comp. = 84
D = 14	$\eta = 0.173$	$\delta = 0.027$	

2.5 Measurement

To respond to the research question raised, the topological changes were measured for the different population structures; preferential, random, and small-world. Thereby, two different scenarios were analysed: growth and steady size of the criminal network. Due to the stochastic nature of the model and the structure of the population, the measurements were done multiple times. Each time, a simulation was done on a newly generated population of the same attachment method. To have a fair comparison between the different attachment methods, the same parameter values were used for the different case scenarios. To achieve meaningful results, each node should converge to its local equilibrium: each node should undergo approximately 100 evolutionary stages during the simulation. The following results show the evolution of the criminal network in the different populations for two scenarios: (i) flat evolution of a CO and (ii) increase of a CO within the population. For this experiment, the reward r_c and c_c values were modified. An extensive analysis of the implications of the other parameters cited in Table 1 can be found in [32]. Thereby, the evolution of the CO in different population structures was compared to one-other[8].

3 Results and Discussion

Figure 2 (left) shows the evolution of a CO with a slight rise in the size of the CO at around 0.015%. One can also notice that with the evolution the standard error increased lightly. In the case of a random structured network, the CO evolved around 0.01%. For a small-world network, the COs were slightly lower with a value of approximately 0.0075%. Using the default parameters, it was possible to trigger an evolution with no particular trend, where the size of the criminal network is approximately constant. Figure 2 (right) presents the evolution of the

[8] The entirety of the code can be found in the following Github repository.

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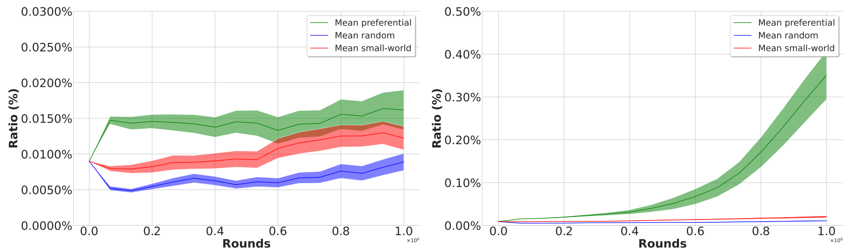

Fig. 2. Evolution of the CO within a population based on the different attachment methods (preferential, random and small-world) using the default parameters (left) as outlined in Table 1. For the simulations on the right, the default parameters from Table 1 were used with $r_c = c_c = 100$. The darker line corresponds to the mean value of 50 games and respective lighter colours correspond to the standard error.

criminal network in the case where the reward factor r_c and damage factor c_c were set to 100. What stands out in this figure is the rapid increase of the CO in a preferential structured network with exponential growth. In comparison, the increase of a CO in a random or small-world network was minimal, despite having the same initial parameters. It is worth noting that the three curves and their standard error did not overlap, which is a strong indication that the trends were significantly different. Criminal behaviour seemed to spread differently across populations. It is all the more interesting to see that criminal behaviour quickly proliferated in a preferential network. The aforementioned results showed that the evolution of the population differed based on its structure. The next step was to examine how the topological structure of the criminal network differs within the different population structures. Figure 3 shows the topological properties of the flat evolution of a criminal network in the different population structures. The three sub-plots visualise the distribution of the properties (secrecy, flow of information, and size of largest component) using a kernel density estimate plot. In the left sub-figure, the secrecy plot shows different distributions between the social network structures. In the case of a preferential network, a uni-modal distribution centring around 45 can be noticed. In the case of a small-world population, a multi-modal distribution with a mean secrecy value of 35 can be seen. In a random world, the secrecy distribution took a very slim peak with a mean value of around 33. A pairwise Tukey's Honestly Significant Differences test [16] was performed with $\alpha = 0.05$ on the distributions indicating that the random and small-world distributions had identical mean. On the other hand, the flow of information plot shows almost perfectly overlapping distributions. Thereby, the distributions resembled a Gaussian distribution with a centre of approximately 0.165. With a p-value> 0.05, it can be assumed that three distributions have the same distribution. The right sub-figure reveals the distribution of the size of the largest component of a criminal network. With a perfect Gaussian curve, the mean size of the largest intertwined criminal network in a preferential structured world was 145. For the small-world network, the distribution was bimodal with a

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peak at 80 and 120. In a random linked network, the size of the largest component was slightly lower with the data centred around 50. The pairwise Tukey indicated that only the preferential data was significantly different from the other two distributions. The results show that despite having the same flow of information,

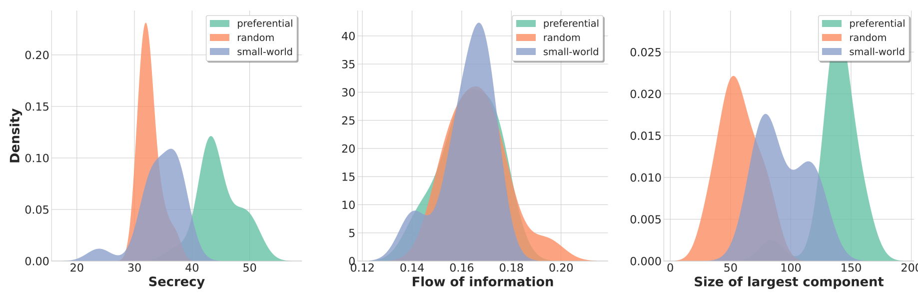

Fig. 3. Measurement of the topological evolution of the criminal network in the different populations (preferential/random/small-world). For each simulation, the games were repeated 50 times with each game played 1e6 rounds. For a fair comparison, the area under the curve was normalised to 1.

a CO in a preferential attachment could increase its secrecy as well as the size of its largest component. As noted by [12], the more secret a network is, the less exposed it will be and the more difficult it would be to shed light on it from a law enforcement perspective. Thus, the results show that in a preferential population, a criminal network can take an optimal configuration, allowing for a high flow of information without compromising its secrecy.

Figure 4 presents the results obtained in case the CO grows within the population. Looking at the secrecy plot over the rounds, one notes a rapid increase in secrecy for the preferential attachment in comparison to the random and small-world. A slight nadir can be noticed in the case of a small-world population. However, after that, a slightly linear increase along the simulation can be observed in the three populations. The flow of information in the middle sub-figure 4 illuminated a more complex pattern where the flow rapidly decreased in the case of the small-world population to stabilise around 0.15. The CO underwent a quick reduction in the flow of information in a preferential attachment before having an almost linear increase along the simulation. For a CO evolving in a random structured network, the flow of information seemed to evolve around the initial value of 0.17. The right sub-figure demonstrates a clear pattern where the preferential data increased exponentially from 95 to around 3500 interconnected MCO in only 1e6 rounds. In contrast, for the random and small-world network, the evolution of the largest component was minimal. Overall, in each sub-figure, the curves seemed to follow unique trajectories. Furthermore, there was little to no overlap in the standard errors in the secrecy and size of the largest component, which could be an indication of significant differences between the curves.

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For the flow of information figure, it is more difficult to assume no overlap. Based on the authoritative reference from [23], a Monte Carlo bootstrapping test was performed to assess the statistical significance. Since it is assumed that the points are correlated for each simulation, block bootstrapping was applied. The hypothesis test stated that for each metric, the distributions statistically differ. For preferential attachment, the size of the largest component increased

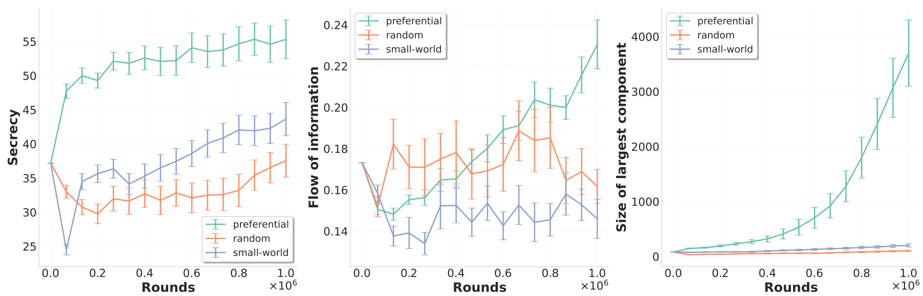

Fig. 4. Measurement of the topological evolution of the criminal network in the different populations (preferential/random/small-world). The left sub-figure shows the evolution of secrecy within a CO. The middle figure shows the evolution of the flow of information in a CO. The right sub-figure depicts the size of the largest connected component of a CO within a population. For this simulation, the default parameters (Table 1) were used with $r_c = c_c = 100$. The line corresponds to the mean value of 50 games with the respective standard error.

faster than the other structures. A possible explanation for this might be that, as pointed out by [3], in a preferential configuration the existence of so-called hubs — highly connected nodes — might ensure the high connectivity between nodes and so easily create giant components. The giant component is judged as being a threat to national security [11]. Moreover, contrary to [12] claims, the results seemed to agree with [8,20] who stated that the presence of hubs increases the efficiency of the CO. While increasing the size of the largest component, the CO was able to maintain or even increase the flow of information/efficiency. Thus, if the preferential configuration is indeed the surrounding structure of a CO, then particular attention should be brought to its evolution. Also, in comparison, the small-world exerted a certain degree of local clustering compared to the random population, which might explain why, in a small-world, the spread of criminal behaviour was slightly more favoured. However, one needs to account for the limitation of the used metrics. As pointed out earlier, the secrecy Equation 2 does take into account only the number of edges and vertices but does not capture the cohesion between these nodes and edges. Therefore a combination of metrics, including the flow of information, was necessary.

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4 Conclusion

In this paper, we introduce a modelling approach to increase the understanding of the evolution of criminal networks given the underlying social network and the social environment. This was accomplished by combining an exogenously given population and an endogenously emerging criminal network: the constructed model raises an interesting aspect that is not yet present in the current literature [4,6,7,12,14,18,33]. The results indicated that the underlying structure of the social network has a non-negligible influence on how the model behaves. Furthermore, the findings advise to take into account the influence of social networks when investigating the spreading of criminal behaviour within a population. It has been shown that a preferential structured population facilitates the dissemination of criminal behaviour while creating an efficient structure in the context of the flow of information and secrecy. The applicability of this research in practice can be ensured by calibrating the presented model against longitudinal data and fine-tuning the model's parameters. The data could correspond, for example, to the social network of a population collected by a national statistical office combined with longitudinal data of criminal networks defined by criminal investigations. The calibration would allow for a close-to-reality simulation, where specific scenarios can be analysed. In this manner, law enforcement can use this simulation to mimic police interventions and examine the resilience of a criminal network and consequently adapt their strategies. The research can be extended by introducing the concept of strong/weak ties to better model the evolving social ties of the surroundings of a criminal network. Additionally, as discussed in Section 3, it is presumed that local clustering in the network could be a potent force for the spreading of a criminal network. Hence, it might be interesting to elaborate on this claim. Local clustering is often characterised by local communities. Thus, an analysis could be conducted on the different communities to ascertain how criminal behaviour spreads within them. This research is theoretical at the moment and aims to provide a scientific basis for further research to build on it. One important criterion is the creation of the population. A limitation of the design is the exogenously imposed ties within the population. Furthermore, the different parameters used for the simulation add uncertainty to it. It is important to bear in mind that the presented findings may be somewhat limited by the huge degree of freedom the simulation entails and the enormous search space generated. In this research specific cases have been analysed and thus cannot be easily translated to more general situations. Nonetheless, the results have shown the importance of taking into account network explicit structures which were not taken into account in [5,12,14,18,21].

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