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Self-Regenerating Crime: The Resilient Network of a Sector of Rio de Janeiro's Drug Trafficking in the 1970s

David Maciel de Mello Neto
Universidade Federal do Rio de Janeiro, Rio de Janeiro, RJ, Brasil

O crime que se regenera: A resiliente rede de um segmento do narcotráfico fluminense em 1970 traça uma análise de rede social (ARS) do narcotráfico fluminense no início dos anos 1970. Depois de revisar a teoria do crime organizado e onde a ARS se posiciona, mostramos como a rede foi construída. As partes restantes exploram o *social embeddedness* da rede, sua topologia e como ela se comporta diante de estratégias de ataque. Os resultados mostram que a rede se organizava em uma topologia comunitária de alta modularidade com efeito de pequeno-mundo e pequena a moderada acoplagem social, potencialmente resiliente contra estratégias de ataque. Na conclusão, traçamos algumas implicações para a teoria sociológica mais geral.

Palavras-chave: análise de redes sociais, crime organizado, tráfico de drogas, violência urbana, acoplagem social

This paper provides a social network analysis (SNA) of Rio de Janeiro's drug trafficking in the early 1970s. After presenting an overview of organized crime theory and the place of SNA in it, I show how the network was constructed. The remaining parts explores the social embeddedness of the network, its topology, and how it behaves in response to attack strategies. The findings show that the network organized itself through a modular topology with small-world effects and a small to moderate social embeddedness, which is potentially resilient to attack strategies. In conclusion, I outline some of the implications for sociological theory.

Keywords: social network analysis (SNA), organized crime, drug trafficking, urban violence, social embeddedness

On organized crime and the position of SNA

In the vast literature on organized crime there is a line of research that stands apart by pursuing an alternative definition of its object. The author who inaugurated this approach was the economist Peter Reuter who, in *Disorganized Crime: The Economics of the Invisible Hand* (1983), switches the focus from organized crime to illegal markets: from entities to activities. This approach involves studying the licit and illicit in parallel. In both domains, economic actors are rational individuals interested in making profits. In both, law of supply and demand determines price formation. The difference is that illegal entrepreneurs face a more restrictive environment: exchanges and contracts are not state-regulated, trust is scarce, credit is expensive, reputation is overvalued and expansion is difficult, given the negative stimuli to advertising business. For these and other reasons, all of them economic in kind, illegal activities tend to be performed either by individual actors or by small groups, most of them fleeting and little structured. There are no 'godfathers.' In the criminal world, smaller is better, so to speak.

A second line of research shares the switch in object inaugurated by Reuter—from entity to activity, from organizations to markets—but swaps the dimension of economic analysis with the political. The pioneer here is the Italian social scientist Diego Gambetta (1996). In describing the Italian mafia, he emphasizes the value that selling protect has in organizing criminal activity. Hence the followers of his approach can be grouped under the label of the Protection Model. These authors remain focused on activity but allow for the formation of enduring and somewhat hierarchical models like *La Cosa Nostra*, closer to the wider public understanding of 'organized crime.'

Nevertheless, the field is marked by pronounced internal divergences. Gambetta and other authors (HILL, 2003; VARESE, 2001) adopt a more symmetric stance in terms of the relation involved in buying and selling protection. They tend to emphasize that this relation is very often not imposed by the political agent—the mafia gang member—but solicited by the economic agent—the trader. Catanzaro (1994), Paoli (2008) and Volkov (2016), meanwhile, are advocates of asymmetry. They argue that this purchase is not a free agreement of exchange, but something imposed by the seller under the threat of violence. Transiting from one pole to the other, the concept of political commodities, defined as the transformation of a political use value into an economic exchange value, outlined by Michel Misse (2011, 2014), resolves this polemic insofar as it allows for a gradation in the use of force. There are more violent, and thus more asymmetric, political commodities, such as extorsion through kidnapping, and more pacific commodities, and thus more symmetric in their use of force, like clientelism.

Whatever the current, all those subscribing to the protection model agrees that it is politics that organizes crime. For Reuter, it is economics. The focus of both is on activity, but the protectionists allow more room for the emergence of entities. The third approach that I shall describe and adopt here—Social Network Analysis (SNA) applied to organized crime and for this reason what I shall also call Criminal Network Analysis (CNA)—assumes an intermediary position. Somewhat unknown to Brazilian sociology, SNA/CNA tends to be more inductive, avoiding a priori judgments on how much organization there really is in 'organized crime.' Along these lines, its objective is to list the possible forms in which activity is structured. It shares this aim with other authors, more focused on constructing typologies of organized crime (ALBANESE, 1989; MINGARDI, 1998, 2014; UNODC, 2002). However, what differentiates them is that while the latter set out from well-established entities—Chinese triads, Salvadorian maras or Brazilian factions—SNA/CNA sets out from the activity to arrive at the form, just as Reuter does and so too, with greater affinity, advocates of the Protection Model.

In general, the results of SNA show that the same illicit enterprise—drug trafficking, for example—occurs under all kinds of structures, ranging from the more horizontal to the more vertical (CANTER, 2004; GALLO, 2014; KENNEY, 2007; NATARAJAN, 2000, 2006). Moreover, in terms of the mechanism of cohesion, despite considering economics and politics to be important factors, they stress the importance that social embeddedness (GRANNOVETER, 1985) has in overcoming distrust and recruiting people with no prior criminal history to engage in illicit activities.

While it shares a concern with activity, with form and with the mechanism of cohesion with the other analytic currents, Criminal Network Analysis differs from them because one of its internal currents, more practice-oriented, aims to describe the network of a criminal organization to identify its weak points and thus formulate efficient attack strategies, which cause maximum damage with minimum effort. In general, its results indicate that the boss is not always the best target (BORGATTI, 2006; REQUIÃO DA CUNHA; GONZÁLEZ-AVELLA; GONÇALVES, 2015). But considering the capacity of the network to recover, even the smartest strategies may be useless (BRINTON MILWARD and RAAB, 2006; DUIJN, KASHIRIN and SLOOT, 2014; EASTON and KARAIVANOV, 2009).

From the brief review above, we can pick out three key questions from the application of Social Network Analysis to organized crime: 1) what role does social embeddedness play in the construction of its social order? 2) what form do these criminal relations present, whether or not it is 'organized'? 3) whatever this structure, is it possible to destroy it? And what is the best way of doing so? Can it recover? The objective of this work is to explore these questions in a specific case: a sector of the drug trafficking in Rio de Janeiro and its ramifications in other states in 1970. The data comes from a document analysis of a military police inquiry set up to investigate drug trafficking in what was then the state of Guanabara, which I present later. Despite its age, the episode is interesting for various reasons. First, because drug trafficking is today one of the main, if not the main, activity associated with 'organized crime' in the public imagination. Second, because the territorial in question is the state where the first drug trafficking 'faction' emerged: the Comando Vermelho (CV), 'Red Command,' born as the Falange Vermelha, 'Red Phalanx,' in the jails of the Cândido Mendes Agricultural Colony. Third, because the episode takes place some years before this latter event. While the CV emerged more towards the end of the 1970s, our case transpired closer to the start of the decade. Here, therefore, we are examining a period in which trafficking was still 'disorganized.' Not only in the public imagination, but even in models like the structuring of criminal activities by Beato and Zilli (2012), which treats this period as one of relative disorganization, inhabited by individual entrepreneurs or primordial clusters of criminals, small in size, little hierarchized and without many conflicts among themselves. Finally, insofar as we can abstract the structure from the content of its relations, the analysis of this network will allow us to delineate a historical and potential future form through which drug trafficking activity became organized and may come to be organized.

Next, I present some SNA concepts necessary to comprehension of the text, as well as my methodological and epistemological position in the field. I also provide a brief description of IPM 63/70 and its critique for us to obtain some idea of the extent of its biases. I then show how the network was constructed. The fourth part discusses how far social embeddedness contributes to the construction of the network's order. The fifth part describes its topology. In the sixth and seventh parts, I test its behaviour in response to two methods of attack: with and without regeneration. I conclude with a synthesis of the findings and their implications for the social theory of order. The general argument is that the case under analysis is organized in a community topology with a small world effect, imbued with weak to moderate social embeddedness, still sufficient, in a hypothetical mechanism of regeneration, to ensure its resilience in the face of external interventions.

Social Network Analysis: concepts, method and epistemology

The first concept is that of the *actor*, the entity composing the network. These actors are connected through *connections*. The set of all the *connections* of this kind form a *relation*. Two actors, connected or not between themselves, form a *dyad*. When another is inserted, a *triad* is formed. A set of actors and the connections between them form a *subgroup*. The *group* as a whole is equivalent to the social network under analysis. Their **size** is measured by the total number of actors, while the *density*[1] compares the total connections observed with the total connections possible. Generally speaking, it is used as a measure of cohesion.

A social network of just one type of relation is called a *simple network*, while those possessing more than one type of relation are known as *multi-layered*. When the actors are all the same kind, the network is considered to be *one-mode*. when there is more than one entity, for example employees and companies, the network possesses two or more modes.

Given the formal characteristics of the connections, a network is classified in three dimensions: 1) *directed v. undirected*, 2) *valued v. neutral*, 3) *dichotomous v. weighted*. Cross classification results in a total of six distinct types, ranging from the simplest, whose connections are undirected, unvalued, and dichotomous, to the most complex, in which they are directed, valued and weighted.

Every network can be visually represented as a *graph*, formed by *vertices* and *edges*. The vertices, also known as *nodes*, symbolize the actors, while the edges symbolize the connections. When the relation is directed, they are substituted by *arrows*.

In a graph, two actors are united by one or more *paths*, whose length is measured by the number of edges between one vertex and the other. The smallest of these paths is known as *geodesic*. In each network, the average of all the geodesics represents its *average distance*.

A subgroup in which all the actors are connected is known as a *component*. Its *diameter* is measured by its *eccentricity*, which is nothing more than its largest geodesic.

Another way to divide up the total network is on *ego networks/ego-centred networks*. Focused on one actor, denominated *ego*, they encompass the connections with the actor's immediate peers and the connections between these peers themselves. The *order* of an ego network is equivalent to its length. A first-order ego network encompasses just the central ego and the others who are at a distance of 1. A second-order network encompasses all those at a distance of 2. Its *neighbourhood* is composed by actors with whom ego is connected, directly or indirectly, depending on the order.

When working with ego networks, the density can be measured only between the members of the neighbourhood, discarding ego. In this modality, the density is known as a *local clustering coefficient*[2]. If the average of these coefficients is taken for all the ego networks, the *average local clustering coefficient* is obtained[3]. A network where this value is high is probably divided into multiple subgroups. One way of identifying these subgroups is through algorithms that devides the network in *communities*: localities where the internal density is higher than the external density. Among all the possible divisions, the best can be considered to be the one that presents the highest *modularity*[4]: a metric that synthesizes the density of the internal connections versus the density of the external ones, comparing the observed network vis-à-vis a randomization of the same.

At the level of the actors, the *measures of centrality* serve to indicate which are the most preponderant. The most traditional is the *degree*, measured by the total number of immediate neighbours possessed by an ego. It identifies the famous *hubs*, the actors whose degree is very discrepant from the others. Another measure frequently used is *betweenness*, which shows how central an actor is within the geodesics between the other possible dyads. An actor with a high betweenness centrality is known as a *broker*.

In terms of my methodological approach within the SNA field, I consider the network to be a method of description and not a form per se. Both hierarchies and egalitarian organizations, as well as those networks between these two extremes, are modes that can be described through the categories and techniques of SNA. In terms of epistemology, I align with the formalist current, as per the division between formalists and relationalists made by Erikson (2013) in a survey of studies from the area. In sum, I set out from the premise that, despite being in a relation of causal reciprocity, form and content can be analytically separated from each other. Consequently, it is possible to approach structure as a matrix of effects on the actions that take place within it. These effects, however, are merely potential in the first instance, their real occurrence depending on a more detailed analysis of their content.

Before I present the source, a caveat is necessary. Although IPM 63/70 is an interesting case in Brazilian history, which would merit an article apart, if not a thesis, here I use it merely as a source, not an object. More details about it can be found in Mello Neto (2018).

IPM 63/70: the source and its biases

The Military-Police Inquiry nº 63 (*Inquérito Policial-Militar nº 63*) of 1970, or IPM 63/70 (AERONÁUTICA, 1971), was set up on July 22, 1970 by Brigadier João Paulo Moreira Burnier, then commander of the Galeão Airbase/RJ, to investigate the ramifications of drug trafficking in Brazil. It derived from another IPM, nº 40/70, which I was unable to find, investigating the sale of narcotics at the entrance to schools on the Ilha do Governador/RJ. As one of these establishments was in a military area, the Brigadier used the localization as an excuse to include drug trafficking, a crime usually covered by the civil police, within the scope of the military investigation. The person at the head of both Inquires was Airforce Lieutenant Colonel Jorge Corrêa. Taken together, the two procedures lasted from June 5, 1970 to April 1971. Their objective, as can be learned from the Inquiry's Final Report and Solution, was to demand criminalization of drug trafficking as a crime against national security, meaning that transgressions, like the crimes classified as political under Brazil's military dictatorship (1964–1985), would be investigated by the Armed Forces. The justification was the alleged existence of an international conspiracy to disseminate drug addiction among Western youths and thus undermine internal resistance to the communist advance in the country.

In the end, the IPM was disqualified for processing in the common courts. Many of the lawyers of the defendants filed lawsuits and *habeas corpus* in the Military Court, arguing that the crime was not under the latter court's jurisdiction. In some documents, the defence lawyers argued that their clients had confessed under torture. As a parallel trial had already taken place in the common courts with the same information, the Military Supreme Court eventually ruled in favour of the defendants.

In the case records for the IPM 63/70, we can identify two main sources of distortions in the data: the communist conspiracy theory and the probable use of torture to extract confessions.

The international communist conspiracy theory distorts the data insofar as the statements were steered to prove it. However, in the interrogations there is no mention by either those making the statements or the interrogators of any association of the accused with left-wing organizations. Those indicted do not speak about the topic, nor are they asked about it. Consequently, the communist plot theory is probably a pragmatic alignment of the facts with the tacit expectations, moral values, and objective rules to produce a desired outcome. Because of this discrepancy between the objectives of the IPM—the criminalization of drug trafficking as a crime against national security—and what is actually said in the interrogations, it can be surmised that this conspiracy theory is not a major source of distortion to the facts.

As an investigation technique, the main problem of torture is producing false evidence. The person under interrogation, to stop the suffering, readily confesses involvement or invents what they believe the interrogator expects to hear, even if they know nothing about the case. The subject is arrested first and their guilt established later, whether or not they are actually guilty.

Here I cannot entirely reject the risk that torture may have distorted the evidence. Neither would I wish to do so, given that it might provide support for its effectiveness. It is very possible that many of those indicted had admitted to being traffickers just to survive. All that can be done here is to provide some reasons why this distortion is not complete.

Firstly, the confession of "guilt-without-being-guilty" tends to be more frequent in investigations that seek to "close a case." As Mingardi (2000) shows, it forms part of the day-to-day work of civil police stations where there is the imperative of showing that they're doing their job. Once they find—or produce—whoever committed a crime, no further investigations are made. The objective is merely to maintain bureaucratic normality. IPM 63/70, though, was an extraordinary case with a large dose of 'moral entrepreneurship,' as Becker (2008) defines the latter: the inquiry's proponents sought to create a rule—a new criminalization of drug trafficking. Hence, if they wanted to provide grounds for their call for a new morality codified in law, they would have to show the extent of the supposed evil that they wished to combat. They could not remain limited to a single case, whether or not it involved a 'real' trafficker or just a scapegoat sacrificed to satisfy everyday demands.

Secondly, looking from the present back in time allows us to attest that there is some truth in the content of the IPM. In its pages appear some notorious figures from Rio's drug trafficking past, such as Milton Gonçalves Thiago, nicknamed 'Cabeção' (Big Head), owner of a *boca-de-fumo* (drugs salespoint) in Rocha Miranda (AERONÁUTICA, 1971, pp. 635-637); Sérgio Manoel Thadeu Neto, 'Serginho do Pó' (Powder Serginho), a dealer who ran the drug trafficking in Morro do Juramento (*Idem*, *ibid*., pp. 1341-1343); Antônio José Nicolau, 'Toninho Turco' (Tony the Turk), one of Rio de Janeiro's biggest cocaine wholesalers in the 1980s (*Idem*, *ibid*., pp. 2158-2159); Anísio Abraão-David, or 'Anísio de Nilópolis,' boss of an illegal gambling network and patron of a samba school (*Idem*, *ibid*., pp. 1369-1370; 1503-1505).

Thirdly, when compared to other sources of the same type, the IPM comes out better. Civil police inquiries into drug traffickers from the same period[5], consulted for this research, were typically based on statements from police and drug users only. In IPM 63/70, however, those testifying are involved in the activity. These discourses refer to each other and can thus be cross-referenced, corroborating each other or not. This oral proof, in turn, is accompanied by more material evidence. In the civil inquiries, the physical evidence of drug trafficking was always a small quantity of drugs caught in the possession of some user. The IPM records the seizure of 3 tons of marijuana, 7.5 kilos of cocaine (a drug then little consumed), 17,000 doses of psychotropics, 400g of amphetamines, and 147 doses of LSD (*Idem*, *ibid.*, 1971, p. 2492).

Finally, the source reveals a mechanism essential to the operation of the so-called 'crime world.' Today a consensus exists in sociology that there is no illegal market without the sale of protection (CATANZARO, 1994; GAMBETTA, 1996; MISSE, 2014; PAOLI, 2008; VOLKOV, 2016). In Brazil, the actors who always performed this role were police officers, both civil and military. Yet none of the other inquires make any mention of police involvement in drug trafficking. The IPM, however, contains lists with the name of police officers, followed by sums, which represent the amount paid in kickback (AERONÁUTICA, 1971, pp. 623-626, 1341-1343, 1503-1505).

For these and other reasons, we can consider the content of the IPM 63/70 at least credibly consistent with what actually happened. My objective here is not to reconstitute the real truth, an aim pursued in the Brazilian inquisitorial tradition (Kant de Lima, 1989). My intention, rather, is to construct a case that is not based solely on theoretical deductions. A case that, even if the available empirical data is minimal, is good enough to think about what is understood by 'organized crime.' A case from which it is possible to extract a form to be described and delineated.

Constructing the network: codification of relations and delimitation of borders

In the Inquiry records, Lieutenant Colonel Corrêa says that suspects were used to reach others, then reach others, and so on (AERONÁUTICA, 1971, p. 2526). This is a difference in relation to the civil police inquiries that the head of the inquiry stresses in the Final Report, when stating that "…for the head of the Military-Police Inquiry, the drug and narcotic addicts had the status of informants, a vehicle through which to arrive at the big, medium and small dealers" (*Idem*, *ibid.*, p. 2526). This procedure is similar to biased sampling methods, like snowball sampling (GOODMAN, 1961) or respondent-driven sampling (HECKATHORN, 1997). Though they are unlikely to produce representative samples, they are excellent for the study of hidden populations like drug traffickers. Moreover, they are well suited to the construction of social networks (WASSERMAN and FAUST, 1994).

The information needed to elaborate the network was taken from two types of documents contained in the IPM 63/70: the Terms of Defendant Questioning (TPI) and the Terms of Witness Inquiry (TIT). Both follow the same pattern: they begin with the transcription of the data, time and location where the statement was being given, who was acting as the clerk, and who was heading the inquiry. Next comes a description of the deponent: age, names of parents, marital status, place of birth, and profession, not necessarily in that order. Afterwards the person being questioned talks about his/her involvement in, or knowledge of, drug trafficking: when he/she began dealing, who he/she bought from and for how much, who he/she sold to and for how much, who else he knew who was also a dealer, and how he/she operated. Over the course of the report some questions request circumstantial clarifications. The interrogators ended by asking whether those accused had anything to say in their own defence. If the informant is a witness, it is merely recorded that he had nothing more to say and no further questions were asked.

In the TPIs and the TITs, each person interrogated speaks about his relations with the people he knew and the relations between them. The figure that emerges from this account is a first-order ego-centred network. Consequently, the final network is equivalent to the overlapping of the ego-centred networks of all the deponents.

After the ample work of cataloguing and removing duplicates, I extracted 1,285 names cited in the testimonies of the 197 deponents. As well as those accused and witnesses, this list includes unlocated people, that is, individuals whose testimonies are not found in the inquiry records. Next, I identify all the connections between them. Initially, I remained as close as possible to the documental record. An except indicating, for instance, that individual A bought marijuana from B was codified as 'marijuana purchase.'

In all 182 different types of relation were codified. The problem is that 182 relations are too many. As many are commensurable with each other, they were grouped into four more general categories.

1) *Affinity*: Indicates a personal connection or some prior experience in common. It functions as a background relation that serves to construct other ties and/or reinforce obligations.

2) *Conflict*: A broader category that encompasses all those in which a misunderstanding exists, resulting in a collapse of reciprocity and/or a dispute.

3) *Coordination*: These relations involve joint action for the pursuit of shared objectives. They may be horizontal or hierarchical, transitory or permanent.

4) *Flow*: Expresses transfer of a resource, which may be tangible or intangible. Drugs, money and other goods are examples of tangible resources, while information, for instance, is intangible. The sale of protection, considered as a political commodity (MISSE, 2014), also belongs to this category.

Having categorized the relations and identified the actors, there appears a classic problem in Social Network Analysis: the delimitation of borders. Without clear criteria being set for belonging, a network may ultimately include all the connections between all the planet's inhabitants. To resolve this problem, diverse expedients exist, the two most common being the nominalist and realist methods (LAUMANN, MARSDEN and PRENSKY, 1983). In the former, the researcher defines the borders based on research questions and the theories used. In the latter, the decision of where the network begins and ends is left to the research subjects. In other words, to the information source. Here I have adopted a mixture of the two.

As my research object is drug trafficking, the first condition was for the actor to perform something linked to the activity, directly or indirectly. I include not only drug dealers, but also the police who sold protection to traffickers. Individuals who did not directly handle narcotics, but acted as brokers, placing interested parties in contact, were included because they were important to the manufacture of connections between traffickers. Those who neither sold nor bought drugs but acted in their preparation or transportation, meet the requirement insofar as they assist the primary activity.

This is the nominalist part of the delimitation of the network's borders. The realist part derives from the observation that the IPM was directed at arresting traffickers, not users. Those who were users only, therefore, appear in smaller numbers than what would be expected. To correct this bias, I opted to exclude those who only consumed drugs.

Finally, a simultaneously nominalist and realist criterion. Among the 197 accused and witnesses located and the other 1,088 unlocated individuals, I opted to include both since some of those who were not found or whose testimonies were not transcribed in the records proved to be as or more important than the others in structuring the network.

Put succinctly, the criterion for eligibility for inclusion within the network border can be defined as follows: the network comprises all those actors who, located or not by the IPM, exercised some activity linked directly or indirectly to drug trafficking but who were not just users. Among those who met this requirement, I included all four relations at the more general level. In Table 1 shows a cross-classification of located and eligible.

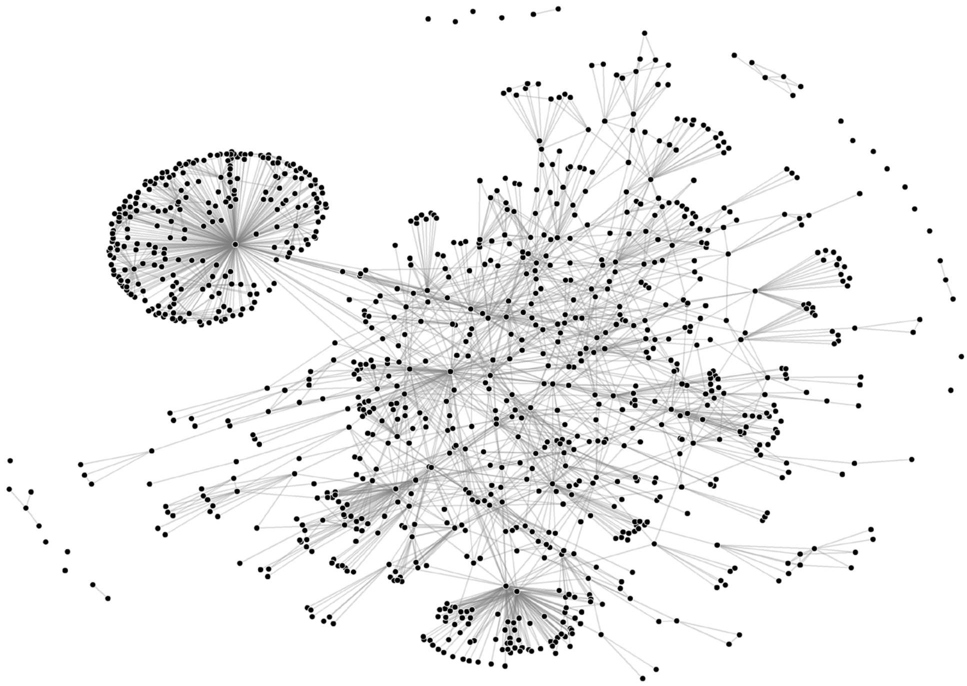
Table 1: Localized v. eligible

	Eligible	**Ineligible**	**Total:**
Located	161	36	197
Unlocated	886	202	1.088
Total:	1,047	238	1.285

Source: IPM 63/70. Author's extrapolation.

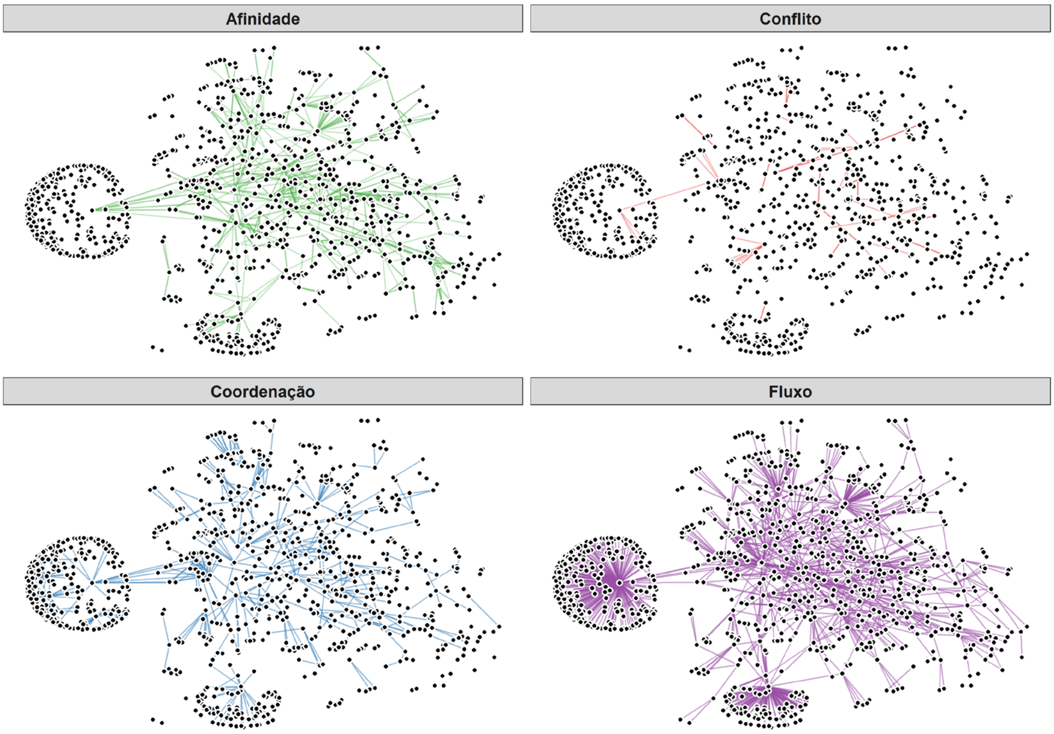
The outcome is a one-mode, dichotomous, undirected and multi-layered network, the object of analysis of the following sections. With this aim, I turned to the R software environment for statistical computing (R CORE TEAM, 2019). The main packages used were *igraph* (CSARDI and NEPUZS, 2006) and *sna* (BUTTS, 2016), both designed for Social Network Analysis. Additionally, I also made use of the *tidyverse* suite (WICKHAM *et al.*, 2019), employed principally to handle databases and plot graphs. In Figure 1, for example, it is reduced to the 1,047 eligible actors, diagrammed using the Fruchterman-Reingold algorithm (FRUCHTERMAN and REINGOLD, 1991). In this figure we can observe the dominance of a gigantic component, with 1,013 actors, surrounded by another five smaller components, 6, 4, 3, 2 and 2 in size, and another 17 isolated actors. Since the largest component congregates the majority of actors and connections, the analyses will be limited to it. Figure 2 shows this component separated by the 4 layers of more general relations. As can be seen, conflict is a minoritarian relation. Despite being a potential indication that, at the time, there were few disputes between drug traffickers, I shall leave it aside, at least in this work. Here I focus on the mechanisms of cohesion rather than incohesion.

Figure 1: Graph of the network for eligible actors



Source: IPM 63/70. Author's extrapolation.

Figure 2: Graph of the largest component separated by the 4 layers of relations



Source: IPM 63/70. Author's extrapolation.

Social embeddedness: form and content in the construction of order

The network with the largest component possesses a size of 1,013 actors, united by 5,018 connections. Its density, calculated by flattening the multiple layers into a single one to avoid overlapping edges, is just 0.4%—an extremely small value, representative of low cohesion, but expected since large networks tend to be sparse and because illegal activities like drug trafficking tend to have a lower density to avoid exposing themselves too much.

Although an important indicator, the metric is deceptive since it fails to show how this solidarity is distributed at local level. A better way of exploring solidarity, therefore, is through social embeddedness (GRANOVETTER, 1985), a hypothesis that sets out from the classic Hobbesian problem of order: if individuals are selfish, only ever thinking about themselves, how is it possible for predictability and relatively harmony to exist in everyday life, without people killing each other in a fierce competition over resources? Hobbes's (2003[1651]) answer to the question was authority: what prevents a reversion to the state of nature is the sovereignty of the Leviathan. Classical economics pointed to the mutuality of interests found in the market, like the baker, brewer and butcher of Adam Smith (2010[1776]). Left to run according to its own devices, the market achieves equilibrium and everyone has their needs satisfied. Sociology, in Durkheim (2007[1895]), opts for values and customs. It is the moral collective, which individuals incorporate during socialization, that ensures peace. People do not attack their peers not because it harms their interests or because they fear punishment from someone all-powerful. They do not do so simply because they introjected the belief that to attack one's peers is wrong.

For Mark Granovetter (1985), the three classic responses to the problem of order are flawed insofar as they consider an atomized subject whose choices occur outside the immediate context. Where they differ is in how each of them imagines this process. Hobbes and classical economics set out from the undersocialized individual, whose pursuit of his or her own interests is the only guide. Sociology tries to resolve the issue through morality, but the result is someone without the capacity for agency, who ends up acting mechanically, as a mere transmission belt of something that was inculcated in them. Granovetter proposes a solution midway between the undersocialization of the former and the oversocialization of the latter. His response is to consider action to be embedded in a network of relations in which actors monitor each other and thus succeed in generating trust. If someone wants to transact with someone else, but does not know if the person is honest, they can ask a third party whom they trust and who has already transacted with the person to learn about the latter's reputation. If A trusts B and C trusts A, C may also trust B.

In other words, 'any friend of yours is a friend of mine.' The classic saying captures the underlying idea of social embeddedness: transitivity. According to this idea, some types of relations can transfer their properties through the mediation of one of the points in a triad. However, the mechanism cannot be seen as either reductionist or exclusivist. Granovetter emphasizes that it an unnecessary, insufficient condition with levels of gradation (1985, p. 491).

In a criminal network in which the actors cannot resort to the legal system to resolve conflicts, embeddedness can be one of various solutions to the problem of trust. In our network, it can be explored in two ways. The first, on the content side, takes into account the overlapping of two different types of connections. Insofar as a connection of 'coordination' or 'flow' overlaps with one of 'affinity,' therefore, it is possible to affirm that a utilitarian relation grafts itself onto another of a social kind, which carries with it a morality regulating the other. Generalized for the group as a whole, it is possible to say how much the layers of 'coordination' and 'flow,' respectively, are 'embedded' in 'affinity.'

Meanwhile, the second operationalization takes place on the side of form and ignores the content of the relations. It is based on the idea that egos whose neighbourhoods possess many internal connections have their actions strongly monitored by their peers. Hence they betray one of them, the others will quickly know, since they are also inter-related. To operationalize it, I use the average local clustering coefficient. The premise is that the larger it is, the more the actors will be inserted in their respective neighbourhoods, such that they monitor each other's actions and, for this reason, possess less opportunities to act in bad faith.

On the side of content, the results show us that 16% of the coordination connections and 8% of the flow connections overlap with the connections of affinity. A low percentage in both cases, but indicative that embeddedness is higher when the actors cooperate than when they exchange resources with one another.

One potential criticism is that the calculation ignored the informants' capacity to hide. It is unlikely that a deponent has admitted everything that he knew in his statement. Consequently, the results obtained may be less than expected. To respond to this potential objection, I cross-referenced information from one deponent with information from others that he knew. Through this expedient, I concluded that a suspect would manage to conceal under interrogation, whether deliberately or because he forgot, around 33% of the connections in his neighbourhood with a standard deviation of approximately 20%. Taking into account this average potential concealment of 33% and considering also that these concealed ties are connections of affinity that overlap with flow and/or coordination connections, the estimates for overlapping increase by around 1/3. Consequently, we would have approximately 21.3% of coordination connections overlapping with affinity connections and 10.6% of flow connections. If we are even more radical and raise the percentage of concealed ties to 53%—a value that includes the average plus one standard deviation, which is around 20%—the results add up to a little more than a half and reach 24.7% for coordination and 12.4% for flow. Despite appearing low in absolute terms, it should be taken into account that social embeddedness divides space with other causal mechanisms, such as the reciprocity of interests, the threat to use force and interiorized morality.

On the formal side, the results are stronger. The average clustering coefficient reaches 0.74, with a high standard deviation of 0.35. The median of 1 indicates that there are deviant values that on average influenced downwards. At the same time, around half of the ego-centred networks present a maximum clustering coefficient. It should be stressed that 167 of the 1,033 actors were removed from the calculation, since they were linked to just one other actor.

In sum, both the formal side and the content side of Rio's criminal drug trafficking network present considerable social embeddedness, although it is not the only mechanism existing in the production of order.

Form: community topology as a small-world effect

In Social Network Analysis, averages of distances serve to ascertain the potential for circulation. The premise is that the smaller they are, the quicker resources can be allocated. In the drug trafficking sector in question, they will be considered as indicators of the potential circulatory efficiency of the illegal market.

Our network has a diameter of 11 edges with an average distance of 4.24, median of 4 and a standard deviation of 1.32. The proximity of the median on the average, combined with the low standard deviation, less than half of the first, are indications that the distribution of geodesics approximate a normal curve. Thus, around 95% of cases are two standard deviations from the average for each side. It is possible to say, therefore, that the majority of actors are united by paths containing between 2 and 6 edges. With one to five intermediaries, almost all the others can be reached.

Combined with the high clustering coefficient already observed, the short distances suggest that the network possesses a small-world effect—something that, according to Watts and Strogatz (1998), is characterized by the low average distance of a network generated at random with the high average clustering coefficient of determined networks. Hence, if the small-world is located between the completely random and the completely determined, the network under analysis should present an average distance similar to randomized and, at the same time, a much higher average clustering coefficient.

To conduct the test, I generated 1,000 random graphs following the Erdos-Rényi model (ERDOS and RÉNYI, 1960), in which the dyads are connected in accordance with a uniform distribution and reflexive connections—that is, actors who are linked to themselves—are not permitted. All of them had the same size of 1,013 actors and the same 2,257 edges of the largest component observed—when simplified from a multilayer network to a simple network.

After simulating these 1,000 networks, I calculated their average respective distances and average local clustering coefficient. The average of these averages are, respectively, 4.69 and 0.005. I recall that our network of drug traffickers presents an average distance of 4.24 and an average clustering coefficient of 0.74. Thus, the average distance observed is close to the simulated value, while the clustering is much higher in the observed case than in the simulated case. Consequently, the results reinforce a strong conviction that the observed graph has a small-world effect.

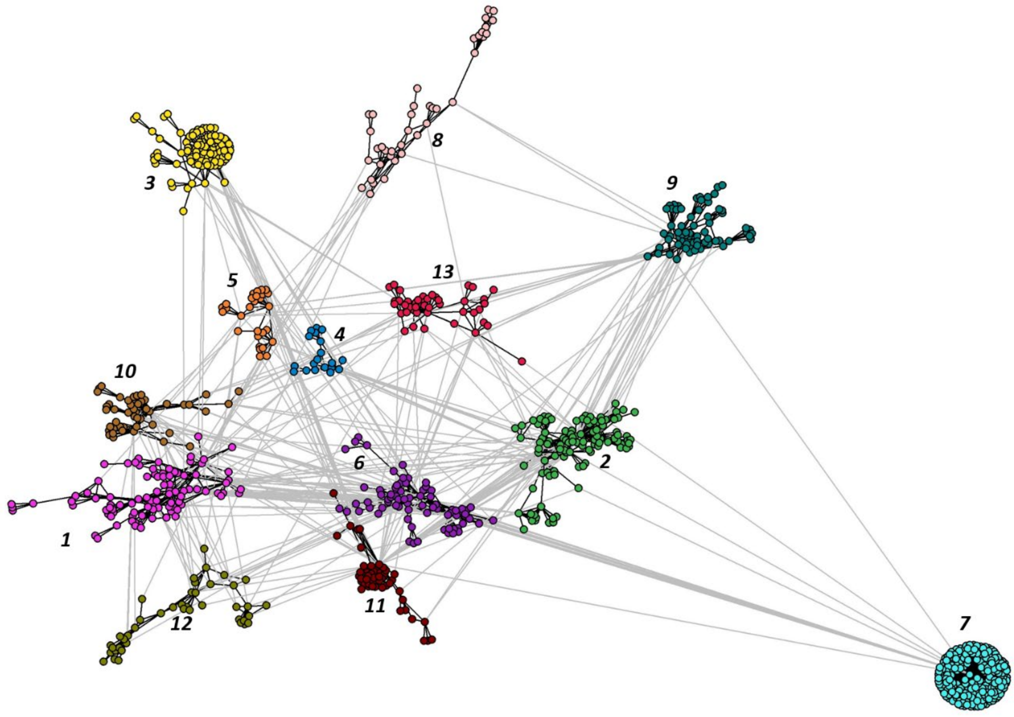
There is more, though. Short average distances and high local clustering suggest that the network is organized in nuclei where the internal connections are denser than the external ones. In Social Network Analysis, these kinds of zones are known as communities (BARABÁSI and PÓSFAI, 2016). Among the diverse methods available to verify and separate a network of communities, I selected modularity, presented above. It varies between -1 and 1, -1 being when each node is a distinct community and 1 being when all the modes belong to the same community. In the positive spectrum, values up to 0.22 indicate that it is not possible to identify whether there are communities or not in the observed graph, since the result is not very distant from the completely random. But above 0.41 we already have clear indications that there is a well-defined structure of communities (DANON *et al.*, 2005).

More specifically, I used modularity through the application of the Louvain algorithm (BLONDEL *et al.*, 2008), whose target is to find the partition in which this metric is the maximum possible. I chose this rather than others because it frequently results in an excluding partition, in which each actor belongs to just one community. The procedure begins in a state in which each node is a specific community, thus with a modularity value of -1. Next, the algorithm evaluates the gain in the metric as one node is grouped with some of its neighbours. Among all those possible, the pair that most contributes to the gain in modularity is reduced to a single node. The process is repeated with all the nodes until there is no more increase in modularity. The network of actors is then reduced to a network of communities. The algorithm continues to verify whether it is impossible to raise the modularity even higher if these groups are joined with each other. Finally, when it is no longer possible to increase the metric, the iteration is interrupted and the result is returned.

On being applied, the algorithm returns a partition into 13 communities, with a modularity of 0.71. Going by the above criteria, our network presents a clear community structure. Below I plot the graph of the largest component again, but this time so as to highlight the division into subgroups. Once more I use the Fruchterman-Reingold algorithm, with the difference that I attribute weights to the intra-community and inter-community edges, such that the former attract each other and the latter repel each other. Those coloured light grey represent the connections between the subgroups. They make up 253 (11.5%) of the 2,195 edges of the network, when this is converted from multi-layered to simple, and are intermediated by 175 of the 1,013 actors (17.2%).

In sum, the network presents a community topology, distributed into 13 subgroups, clearly distinct because of the high modularity. Additionally, it possesses a small-world effect, which shortens the distances and, potentially, facilitates the circulation of resources and the mobilization of peers.

Figure 3: Community structure in the Rio drug trafficking network of 1970



Source: IPM 63/70. Author's extrapolation.

Attack and regeneration: network resilience

From a practical viewpoint, detailed knowledge of the structure of a network is important should one wish to intervene in it. Community networks with small-world effects are resistant to random external attacks because they have few central points of support. However, once it is known who performs these mainstay functions, a directed attack is capable of breaking the network with just a few removals.

The most traditional attack methods identify these key actors through measures of centrality. The most commonly used are those of degree and betweenness, which show, respectively, who are the hubs and the brokers. A more recent strategy (REQUIÃO DA CUNHA, GONZÁLEZ-AVELLA and GONÇALVES, 2015) applies the Louvain algorithm to select the targets. Instead of removing those with a higher degree or betweenness, it opts for those who intermediate the intercommunity ties, which here I have called *bridges*.

We have, therefore, three methods of selecting targets: by hubs, by brokers, and by bridges. To design an attack algorithm, it is just necessary to define an objective. The most traditional attacks seek to fragment the network into the highest number of components possible with the fewest attacks. However, this is not always the best strategy. If the result is a more fragmented network but still with the prevalence of a large component with short geodesics, the rapid flow between members will persist. An alternative is to aim to increase average distances—a plausible objective in a community network with a small-world effect, characterized precisely by the efficient potential circulation. Hence, it suffices that the paths are long for contact between actors to be virtually impossible. In this case, the objective is not to dismantle criminal groups, but the circulation channels that structure an illegal market.

To test which attack method is the most effective, I developed three attack algorithms. Although the selection of the targets varied, they follow the same protocol, described below:

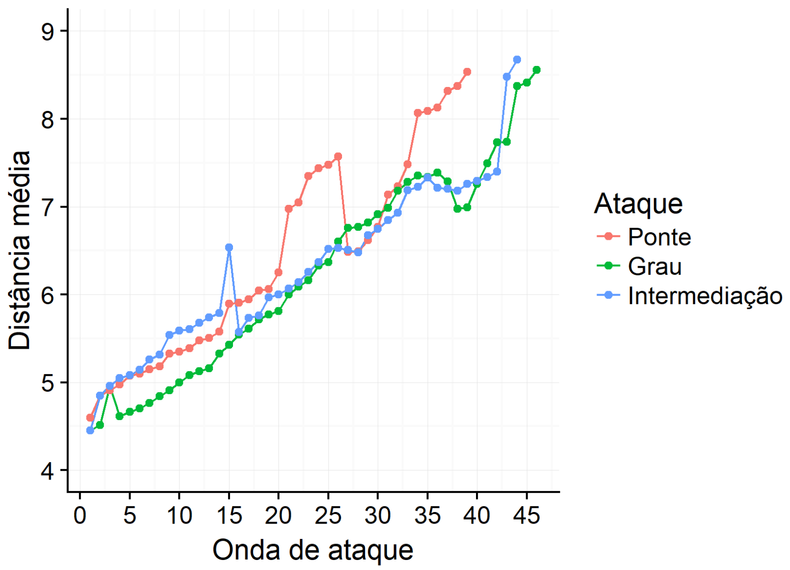
1) *Selection of targets*. Attack by hub calculates the degree centrality for each actor and sorts the results in decreasing order. Attack by broker does the same but with betweenness centrality. Attack by bridge sorts the actors in decreasing order by total intercommunity edges. Here I take a different approach to the method of Requião Cunha et al. (2015), who order their targets by betweenness centrality.

2) *Attack*. The first actor from the list is removed.

3) *Identification of the largest resulting component after the attack*. If the following target is not found in it, a jump is made to the next on the list.

4) *Calculation of average distance*. If this is smaller than double the distance of the initial average distance, which is 4.24, the previous procedures are repeated. If equal to or higher than double, the attacks cease.

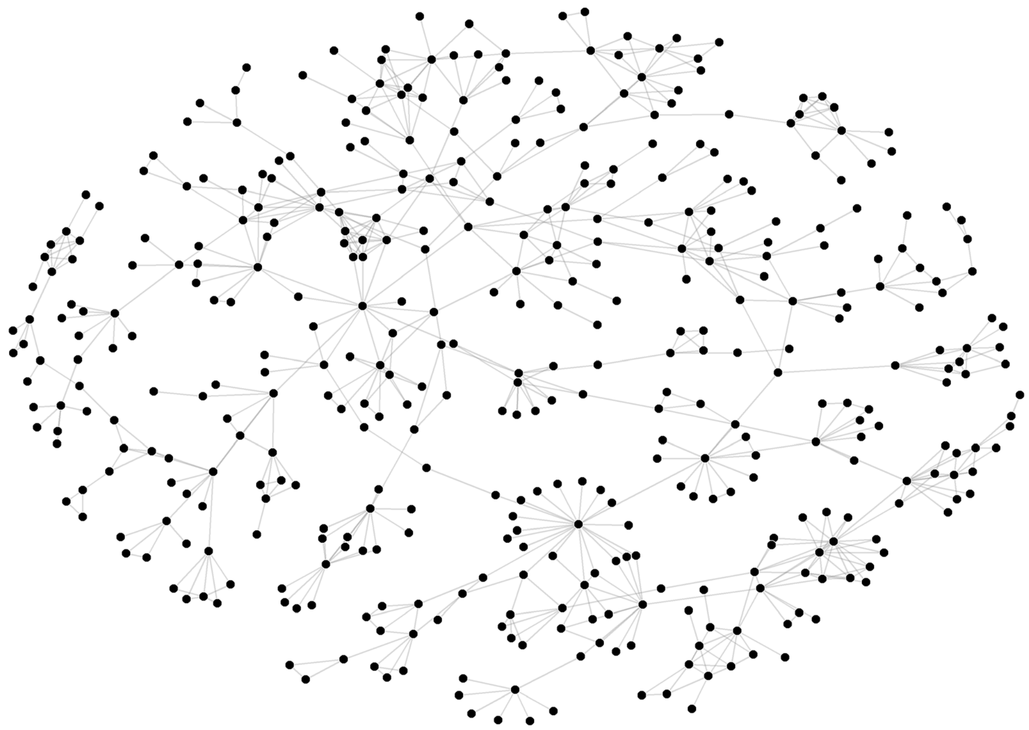
Figure 4: Performance of the attack methods



Source: IPM 63/70. Author's extrapolation.

In Figure 4 we can see that the bridge attack was the most efficient, since the initial distance was doubled with 39 attacks. Next, broker attack attained the same result after 44 iterations. Hub attack, after 46. Figure 5 shows the largest component after the removal of 39 bridges. We can note its sparseness compared to the graph shown in Figure 1.

Figure 5: Graph of the largest component after bridge attack



Source: IPM 63/70. Author's extrapolation.

Although effective, the problem with the attack algorithms designed previously is that they presume that the actors are passive beings, incapable of reacting to the problematic situations that jeopardize the stability of order. They do not consider the possibility that, on finding themselves disconnected, the neighbours of the removed actor try to reconnect and thus end up regenerating the network. To explore this scenario, I developed a recovery algorithm based on two mechanisms, observed in an analysis of the content of some relations. These are transitivity in affinity relations and succession in coordination relations.

To illustrate the former, we can imagine the situation in which B supplies drugs to A, who in turn resells them to C, a smaller dealer. As well as the commercial link, A has a longstanding friendship with B and C, who do not know each other. After a police raid, A is arrested. B loses his client and C loses his supplier. Consequently, B has to find a new buyer and C has to find a new seller. If while searching for a new contact, they meet each other and discover that, as well as the utilitarian connection that both had with A, they also possess a connection of affinity, they know that they can trust the other. In terms of the second, the succession mechanism in coordination mechanisms, this occurs when one actor is removed from the network and his subordinate or partner assumes his place. Returning to the example of A, B and C, we can imagine that A is the owner of a drugs sales point and B and C are his sellers, popularly known as *vaposeiros*. A ends up arrested in a police raid. But B, as well as knowing the clientele, since he was the one who sold the drug, also knows A's suppliers, unknown though to C. Consequently, it is not impossible that B assumes the place of A in the drugs sales point. In this case, even if there is no social embeddedness in the coordination relations or the affinity relations, coordinated collective action itself contains a socialization in the everyday activities of drug dealing. Over time, a subordinate learns from whom to buy, to whom to sell, where to sell, and for how much. Later, if he does not begin his own business, he can take the place of the boss.

These two mechanisms, regeneration through transitivity and through succession, were combined in a local regeneration algorithm, described below:

1) After removal of an actor, all his alters are identified, those with whom the person removed has relations of affinity or coordination.

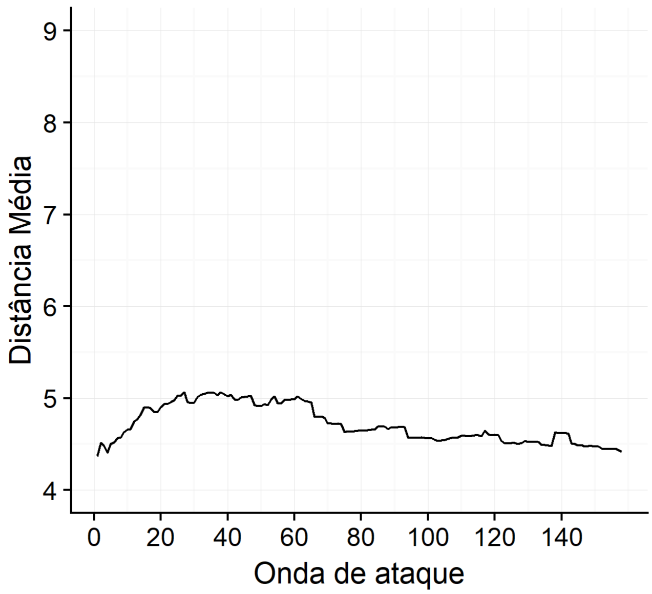
2) All the possible edges are generated among the identified alters.

3) Each generated edge is added to the network, with a probability equal to the local clustering coefficient of the removed target. The premise here is that the higher the coefficient, the higher the formal social embeddedness of the ego-centred network and, therefore, the higher the potential trust between ego's peers.

I combined local regeneration with the bridge attack. Since the recovery is probabilistic, I used the algorithm 100 times to obtain more robust results. Figure 6 shows the evolution of the average distance after each attack wave, combined with regeneration. Even with the removal of all 175 targets, the bridge attack was unable to double the average distance. Table 2 compares the metrics of the largest component before and after the attack with regeneration. In Figure 7 we see how the largest component ends up after its recovery.

Additionally, I constructed an interactive visualization of all the procedures undertaken so far, which can be seen at the link http://pitacossociologicos.com/rede/rede.html. For this, I used the JavaScript D3 library (BOSTOCK *et al.*, 2011). In it the network was simplified to a one-dimensional, undirected and dichotomous graph. The points are actors and the edges are connections. After opening the page, the position of the points is calculated using the same principles as the Fruchterman-Reingold algorithm (FRUCHTERMAN and REINGOLD, 1991). The user can zoom in or out using the mouse or touchpad, as well as drag it by clicking a blank space and moving the arrow. Placing the arrow over an active point displays a text box with some information on the actor: name, the community to which he belongs, the drugs sold and the roles he performed. The search box, with an autofill function, allows the localization of specific actors by clicking 'search.' By clicking on a point, the actor and his/her connections are removed. By clicking on 'eligibility,' the ineligible actors are marked in red, representing those who will be removed when the 'remove ineligible actors' button is clicked. The next button, 'largest component,' shrinks the network to the largest component, the object of these analyses. 'Communities' divides the network into the 13 communities identified above. 'Attack without recovery' applies the algorithm in its bridge attack version. 'Attack with regeneration' applies the same algorithm but with mechanisms for regeneration through relations of affinity and cooperation.

Figure 6: Performance of the bridge attack when combined with local regeneration



Source: IPM 63/70. Author's extrapolation.

Table 2: Largest component before and after bridge attach with local regeneration

Largest component	Size	Density	Average clustering	Diameter	Average distance
Original	1,013	0.4%	0.74	11	4.24
After regeneration	411	1.4%	0.47	14	4.45
Variation	- 59.43%	+240,34%	-36.49%	+27.27%	+5.07%

Source: IPM 63/70. Author's extrapolation.

When we look at Table 2 more closely, we observe that density more than triples. On one hand, the increase is expected, since smaller networks tend to be denser. But the regeneration of connections ends up boosting this increase even further. Combined with the fall in local clustering, it seems to indicate that cohesion rises at global level while diminishing at local level. At the same time, the low growth of the diameter and the average distance show that the network's effectiveness in the circulation of resources remains almost intact. Read together, these results seem to show that as the network is attacked and recovers, its actors free themselves from their respective local contexts. Less monitored by their peers, they enter into contact with others, previously unknown. They begin to act more autonomously in a tendency that, ultimately, is similar to a primordial market of individual entrepreneurs, described by some models as the primeval state of organized crime (BEATO and ZILLI, 2012; FELSON, 2009). Hence, smart attack strategies, insofar as they dismantle the community structure groups, may well put an end to the organized crime aspect, but the illegal market survives. Over time, new actors are likely to emerge and the connections change configuration, perhaps even attaining a level of 'organization' higher than the previous state. In the end, any intervention, even the most surgical, is merely an act of *enxugar gelo*, 'drying ice,' futile in other words.

In sum, the network of the analysed sector seems to be higher resilient—a resilience that does not mean the capacity to repel external attacks or avoid problematic situations, but to respond to them creatively on the basis of its surroundings. Imprisonment and violent deaths have always occurred and always will in the crime world. What matters is knowing how to deal with them. Not necessarily to rebuild what was lost, but to adapt to the new reality.

Figure 7: The largest component after the bridge attack combined with local regeneration

Source: IPM 63/70. Author's elaboration.

Conclusion: implications for sociological theory

Responding synthetically to the three questions posed at the start of this work—concerning social embeddedness, form and recovery capacity—it can be said that Rio's drug trafficking in 1970 presented a topology with small-world effects where the social embeddedness of relations of exchange and cooperation in relations of affinity had a weak to moderate influence on network structuring—sufficient, however, to ensure its recovery.

Having fulfilled this initial task, I would like to explore some implications of the results for sociological theory. Firstly, organized crime is too prolific an object to think about a fundamental question of sociology, social order, since it is a limit case: it should not be able to act or operate collectively, given that it is prohibited by law. However, it not only happens and works collectively: it is also maintained despite the constant attempts to eliminate it. Something very distant, therefore, from a Hobbesian state of nature.

Secondly, social order seems to be multicausal. Despite the reviewed theories primarily identifying instrumental rationality and protection policy as primordial causal mechanisms, morality is also present. Whether through the transitivity of social embeddedness, or the socialization enabled by cooperative relations, it ensures the network's resilience.

Thirdly and lastly, social order does not seem to be the unexpected effect of accumulated individual actions, as an extreme ontological individualism would presume, as described by Alexander (1987), nor is it a *sui generis* reality that shapes individual options and choices, as radical ontological holism believes (*Idem*). If the topology of communities with a small-world effect is located between the completely random and the completely determined, social order resides somewhere between these two extremes. Actors possess freedom, but it is not full, since they are inserted in a structure of which complete awareness escapes them, but shapes and constraints their everyday opportunities. They deal with it the whole time, but they can only attain it as far as their immediate connections extend.

Notes

[1] $D = \frac{1}{n(n-1)/2}$, for undirected networks, where n = the number of nodes in the graph. For directed networks, the density formula is $D = \frac{1}{n(n-1)}$.

[2] $C_i = \frac{2L_i}{K_i(K_i-1)}$, where L_i = the number of connections (links) between the neighbours of *i* and K_i = degree of the node *i*.

[3] $\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$, where C_i = the local clustering coefficient and *n* = the number of the nodes in the graph.

[4] $M_c = \sum_{c=1}^{n_c}\left[\frac{L_c}{L} - \left(\frac{K_c}{2L}\right)^2\right]$, where *Nc* = the number of communities, *Lc* = intercommunity connections, L = total connections (links) and *Kc* = total of the degrees of nodes in a community.

[5] Justiça do Estado da Guanabara (1974) e Tribunal de Justiça do Rio de Janeiro (1975).

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DAVID MACIEL DE MELLO NETO (davidmaciel2206@gmail.com) é pesquisador de pós-doutorado no programa de Pós-Graduação em Sociologia e Antropologia (PPGSA) da Universidade Federal do Rio de Janeiro (UFRJ, Brasil). É doutor e mestre pelo mesmo programa e graduado em ciências sociais pela UFRJ.

https://orcid.org/0000-0002-2391-1312

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