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ARTICLES

MULTI-CRITERIA DECISION SUPPORT TO CRIMINOLOGY BY GRAPH THEORY AND COMPOSITION OF PROBABILISTIC PREFERENCES

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ABSTRACT. This study associates graph theory and a multi-criteria decision aid technique, presenting a different process for doing the investigation of criminal networks. In the criminal subject, privacy concerns limit identification. For this reason, the database composed of 110 actors, involving criminals and peripheral characters to the network, was identified by numbers, without names and penalties. The discrimination of critical actors in criminal networks can help law enforcement officers to conduct a more detailed investigation for their disruption. Communication between drug traffickers was transformed into different centrality indices for each actor in their social network. Centralities and actors compose a decision matrix, analyzed by the Composition of Probabilistic Preferences to identify the most relevant actors in the criminal network. Results indicated that the five actors highlighted in the real investigation have a clear distinction of importance in the network, which in a way have been ratified.

Keywords: Social Network Analysis; Composition of Probabilistic Preferences; CPP-TRI

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1 INTRODUCTION

Police intelligence plays a vital role in preventing and controlling organized crime. The success of law enforcement depends, in large part, on the identification of the criminal network, its nature, structure, methods of operation, among others (Ratcliffe, 2016; Tilley, 2016). One of the first studies to explore the so-called "link analysis" in an investigative problem dates back to the pre-computational period, almost two decades before the emergence of the Internet (Harper & Harris, 1975).

Since then, the evolution of data storage, processing and transmission capacity has provided a significant advance in the analysis of social networks, based on graph theory (Wiil et al., 2010). An increasing number of researchers have applied social network analysis to reveal the dynamics of criminal organizations (Fire & Puzis, 2016; Taha & Yoo, 2015). The identification of critical network nodes can be directed by law enforcement agencies for a more detailed investigation and subsequent disruption as a result of the association of these critical nodes with the leaders and main links in a criminal network (Burcher & Whelan, 2018).

In graph theory, the identification of critical nodes can be obtained through measures of centrality, whose values allow to order from the most to the least important network node, for example (Borgatti & Everett, 2006). The different measures of centrality can be especially useful in complex networks, composed of a significant number of actors and links, to clarify vulnerabilities and weaknesses that guide the application of research resources (Burcher & Whelan, 2018).

Although graph theory describes measures of centrality using a few basic categories such as degree, closeness and betweenness, the literature records more than two hundred algorithms for calculating these measures (Bloch et al., 2019; Das et al., 2018; Oldham et al., 2019). Depending on the type of centrality used, it is possible that one node in the network calls more attention than another during the network analysis, depending on the variation of the data. Alternatively, the use of a set of centrality measures to determine a list of key actors in a criminal network can be interesting to offer investigators new options, helping the process of choosing targets to monitor. The use of a set of centralities expands the range of options for the optimized application of resources, which can be a differential to investigations.

In this article, the Caviar Project, an anti-drug operation, was revisited considering several centrality measures, combined with a methodology to multicriteria decision aid (MCDA) (Morselli, 2009). The criminal network was targeted between 1994 and 1996 by a tandem investigation uniting the Montreal Police, the Royal Canadian Mounted Police, the Canadian Police, and law-enforcement agents from England, Spain, Italy, Brazil, Paraguay and Colombia. The purpose of reassessing this real case was to ratify or rectify the existence of important actors in the criminal network, both those identified and those who, eventually, remained hidden from investigators. The motivation to "reopen" this case arose from the fact that investigators exploited only two measures of centrality to analyze the social network, which may have biased or distorted the identification of the main criminals. The proposal to revisit the investigation, through new Operations Research techniques, contributes to the robustness of the process.

Network analysis usually evaluates how actors are connected. In the Caviar Project, analysts used measures of degree and betweenness centralities. Degree centrality emulates a direct connectivity, visibility, and vulnerability within a criminal network. Betweenness centrality shows brokerage positions, revealing a possible sign of strategic involvement in criminal networks (Morselli, 2009). It should be noted that the analysis carried out at the time was not mistaken, but here we suggest new centrality measures and a new methodological approach capable of highlighting other actors also important in the criminal network.

The article also brings an innovative approach to Probabilistic Composition of Preferences for problems of ordered classification (CPP TRI) (Sant'Anna, 2015). This method allows to allocate the actors of a network in pre-selected categories. For example, it is possible to distinguish more and less important actors, considering performance measures in multiple criteria. The CPP TRI algorithm verifies if each actor performs above or below parameters, called class profiles, which best define the categories.

Considering the focus in determining the upper class, instead of choosing a set of class profiles, as in the original CPP TRI, in the present study a series of two-class scenarios with increasing restriction is designed to progressively select the number of upper-class actors. In this way, only actors with the best overall performance in the various measures of centrality remain in the upper class. This procedure gives robustness to the classification procedure, as the alternatives only stay in the main class if they confirm their performance in all scenarios.

This procedure is also interesting because it involves less computational effort, in relation to other variants of CPP. CPP TRI calculates the probabilities of each alternative being above or below one profile at a time, instead of considering all alternatives under each criterion in the calculation of joint probabilities. This reduction in computational effort is useful for dealing with large networks, characterized by thousands (or even millions) of actors and links. Although the Caviar network is made up of 110 actors, the reduction in processing time for calculations with CPP TRI is significant in relation to the original CPP procedure.

2 RELATED RESEARCH ON CRIMINOLOGY

In the field of quantitative criminology, several scientific articles highlight the usefulness of social network analysis to help the elucidation of crimes and identification of key criminals for investigation. Radil et al. (2010) compared the geography of rivalry relations that connect territorially-based criminal street gangs in a section of Los Angeles with a geography of the location of gang-related violence. Tita & Radil (2011) analyzed the spatial distribution of gang violence by considering the relative location of the gangs in space while simultaneously capturing their position within an enmity network of gang rivalries. Davies & Johnson (2015) examined the relationship between road structure and residential burglary risk in Birmingham (UK) via network analysis and betweenness centrality measures. Duxbury & Haynie (2018) studied the network structure of opioid distribution on a darknet cryptomarket, using exponential random graph modeling to evaluate which vendor characteristics explain variation in purchasing patterns. Bright et al. (2019)

examined a methamphetamine manufacture and trafficking network that expanded from small scale social dealing to a large-scale profit-motivated business, using dynamic network analysis to evaluate both overall network structure and actor level characteristics. They highlight that "social network analysis should be used by intelligence agencies and law enforcement agencies to facilitate intelligence collection and to guide prevention and intervention strategies". McCuish et al. (2020) modeled three network structures that separated the variance in the relationship between features of psychopathy and offending into between-subjects and within-individual networks. McMillan et al. (2020) used a variety of descriptive network measures and Separable Temporal Exponential Random Graph Models to find patterns of tie formation across eleven multiwave terrorism networks.

Although the Caviar Project took place in the 1990s, several studies are recurrent on the subject, with the purpose of bringing new possibilities to identify criminal networks. The first studies associating the Caviar network with network analysis methodologies were developed by (Morselli, 2009; Morselli et al., 2007; Morselli & Petit, 2007). Later, Morselli et al. (2013) reported the ability of centrality measures to predict the verdict (innocent or guilty) and the sentence length in years, using the same network. Skillicorn et al. (2014) used spectral embedding to model the Caviar network. Masías et al. (2016) used regression techniques to model criminal trial verdict outcomes using social network measures, exploring the Watergate Case and the Caviar network. Duxbury & Haynie (2019) used an agent-based model to evaluate criminal network resilience by examining network recovery from disruption in an array of different criminal networks and across different disruption strategies, including the Caviar Project. Taha & Yoo (2019) proposed a new forensic analysis system to infer the high-level criminals and short-list the important communication channels in a criminal organization, based on the mobile phone communications of its members.

3 RELATED RESEARCH ON MULTICRITERIA METHODS

Network analysis is a broad area of study, which is based on two variables to conduct the analysis: actors and relationships. The range of methods in network analysis involves quantitative studies, such as social network analysis, and ethnographic studies. In the literature, the methodological procedure followed in this study is called "social network analysis" and "link analysis," to differentiate quantitative analysis from the current meaning of social networks, often associated with Facebook, Twitter, Instagram applications, among others (Alrashoud et al., 2015; Liu et al., 2018). The expression "social network analysis" is now used in this study.

The analysis of social networks, and especially their measures of centrality, combined with MCDA models has been explored in the literature, to identify the most influential actors in a network, based on a varied set of indicators. Several authors have explored, for example, the Technique of Ordering Preferences by Similarity with Ideal Solution (TOPSIS) for this purpose (Du et al., 2014; Fox & Everton, 2013; J. Hu et al., 2016; Kermani et al., 2016).

Associated with TOPSIS for calculating criteria weights or even used in isolation, the Hierarchical Analysis Process (AHP) and its variant with network analysis (ANP) also find applications in research in this area, although a limitation of AHP in networks is the difficulty of dealing with a large number of nodes and links (Choudhary & Singh, 2018; Fox & Everton, 2015; Shoman & Gülgen, 2017). However, note that TOPSIS, AHP and its ANP variant are not MCDA methods designed to face the problem of classifying alternatives in ordered homogeneous groups, defined by an order of preference, such as ELECTRE TRI and CPP TRI. It is also worth mentioning that these MCDA methods are different from traditional clustering methods, not covered in this paper, as they classify the data into ordered groups.

CPP-TRI is a variant of the CPP method. The original model was developed by Sant'Anna & Sant'Anna (2001), and was later expanded in Sant'Anna (2015). CPP is a probabilistic MCDA method, whose variants apply to different problems of multicriteria decision, which include the ordering of alternatives under different points of view for decision making (Gavião et al., 2017), the ordering with Choquet capacities (Souza et al., 2016), the dynamic assessment of alternatives based on Malmquist index (Sant'Anna, 2009), the assessment of regularity based on the Gini index (Gavião, Sant'Anna, & Lima, 2019), among other options that associate these variants (Gavião et al., 2019). In this study, the model of interest is CPP TRI, which performs classification of alternatives in ordered classes pre-defined by the user, also called sorting. (Sant'Anna et al., 2015; Sant'Anna, 2014; Sant'Anna et al., 2016).

The algorithm introduced here seeks to raise a group of actors of greater relevance in a social network through the ordered classification of its actors. Operational Research brings several methods for sorting alternatives, besides CPP TRI. Table 1 compares CPP TRI with other approaches and their variants, based on the main features of CPP. It is not simple to frame a wide variety of methods under similar characteristics, but the attempt is worthwhile to show how CPP is unique in its classification algorithm. This review tracked methods published in the main Operations Research journals and events, but, given the dynamism and creativity of scientists in creating new methods and variants to the existing ones, it may still be omitting some methods.

The main features of multicriteria methods to sort alternatives are highlighted in Table 1. The first columns show the root method on which the variant used for sorting the alternatives is based. The '*data type*' column identifies the degree of certainty attributed to data collected from input sources for modeling, e.g., expert evaluations and raw data. Data represent quantitative values, e.g., crisp numbers, probabilistic measures, fuzzy sets, and rough sets. The '*normalization*' column indicates whether the method requires standardization of the collected raw data, including the use of specific scales. The '*class profiles*' column indicates whether the model requires class profiles to distinguish the thresholds or features of each class. The '*intra-criterion evaluation*' column indicates how the evaluations are employed in the aggregation algorithm, if previously compared to all the others, or part of the others, or if some criteria comparison is initially performed. The last two columns show the first published version of the model and relevant ulterior applications.

Table 1 – Multicriteria sorting methods.

Main family	Variant / Model for sorting	Data type	Normalization	Class profiles	Intra-criterion evaluation	First published version	Relevant applications
CPP	CPP TRI	Probabilistic	Not necessary	Yes	All relative or Partial relative	(Sant'Anna et al., 2012)	(Gavião et al., 2018, 2020; Monte, 2019; Sant'Anna et al., 2015; Sant'Anna, 2015; Sant'Anna et al., 2013, 2016; Sant'Anna et al., 2015; Sant'Anna et al., 2015; Silva et al., 2016)
AHP	AHPSort	Deterministic	Yes	Yes	Pairwise	(Ishizaka et al., 2012)	(Ishizaka et al., 2021; Ishizaka et al., 2020; Ishizaka & López, 2019)
	AHPSort II					(Miccoli & Ishizaka, 2017)	(Assumma et al., 2021; Guo et al., 2020; Labella et al., 2020; Mei et al., 2019; Xie et al., 2019; Xu et al., 2019)
	AHPSort I or II (Fuzzy)					(Krejčí & Ishizaka, 2018)	(Ishizaka et al., 2020; Xu et al., 2019)
	GAHPSort					(López & Ishizaka, 2017)	(Labella et al., 2021)
	GAHPSort II					(Assumma et al., 2021)	Not found
	AHP-K-GDSS					(Ishizaka et al., 2017)	(Lolli et al., 2017)
	ANPSort					(Ishizaka & Pereira, 2019)	Not found
CODAS	CODAS SORT	Deterministic or fuzzy numbers	Yes	Yes	Partial relative	(Ouhibi & Frikha, 2019)	Not found
	CODAS SORT (Fuzzy)					(Ouhibi & Frikha, 2020[a])	(Ouhibi & Frikha, 2020b)
DEA	DEASORT	Deterministic	Yes	Yes	Pairwise	(Ishizaka et al., 2012)	(Qin et al., 2021; Zeng, 2019; Zhou, 2020)
DRSA	DRSA	Rough sets	Not necessary	Yes	'If-then' rules	(Greco et al., 2000)	(Błaszczyński et al., 2021; Boggia et al., 2014; Chakhar et al., 2016; Greco et al., 2007; Hu et al., 2017; Liou & Tzeng, 2010)

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Main family	Variant / Model for sorting	Data type	Normalization	Class profiles	Intra-criterion evaluation	First published version	Relevant applications
ELECTRE	ELECTRE TRI (also TRI-B)	Deterministic	Not necessary	Yes	Partial relative	(Roy & Bouyssou, 1993; Yu, 1992)	(Biluca et al., 2020; Cervi & Carpinetti, 2017; Dehraj & Sharma, 2020; Fontana & Cavalcante, 2013; Gonçalves et al., 2021; Şahin et al., 2021; Szajubok et al., 2006; Trojan & Morais, 2012)
	ELECTRE SORT					(Ishizaka & Nemery, 2014)	Not found
	ELECTRE TRI-nB					(Fernández et al., 2017)	(Bouyssou et al., 2020; Fernández et al., 2019, 2020)
	ELECTRE TRI-C					(Almeida-Dias et al., 2010)	(Bouyssou & Marchant, 2015; Costa et al., 2019; Figueira et al., 2011; Govindan & Jepsen, 2016; Pereira et al., 2019)
	ELECTRE TRI-ME					(Costa et al., 2018)	(Costa & Duarte, 2019; Pereira, 2019)
	ELECTRE TRI-nC					(Almeida-Dias et al., 2012)	(Almeida-Dias et al., 2012; Costa et al., 2018; Doumpos & Figueira, 2019; Fernández et al., 2020)
	ELECTRE TRI-Rc					(Kadziński et al., 2015)	(Rezaei et al., 2017; Rocchi et al., 2018)
	ELECTRE TRI-NG					(Sobral & Costa, 2012)	Not found
PROMETHEE	FLOW SORT	Deterministic	Not necessary	Yes	Pairwise	(Nemery & Lamboray, 2007)	(Nemery & Lamboray, 2008; Remadi & Frikha, 2020; Sepulveda et al., 2010)
	FLOW SORT GDSS					(Lolli et al., 2015)	Not found
	P2CLUST					(De Smet, 2013)	(Rosenfeld & Smet, 2019; Sarrazin et al., 2018)
	PROMSORT					(Araz & Ozkarahan, 2005)	(Küçükbay & Metin, 2019; Silva & Alencar, 2019; Viana & Alencar, 2015)
	PROMETHEE TRI		Yes (preference functions)			(Figueira et al., 2005)	(De Smet, 2019; Garcez et al., 2012)

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Main family	Variant / Model for sorting	Data type	Normalization	Class profiles	Intra-criterion evaluation	First published version	Relevant applications
GAIA	GAIA SORT	Deterministic	Yes	Yes	Partial relative	(Nemery et al., 2012)	Not found
MACBETH	MACBETHSort	Qualitative assessment	Not necessary	Yes	Pairwise	(Ishizaka & Gordon, 2017)	Not found
SMAA	SMAA-TRI (SMAA + ELECTRE TRI)	Ordinal, Probabilistic or Fuzzy numbers	Not necessary	Yes	Partial relative	(Tervonen et al., 2007)	(Angilella & Mazzù, 2015; Jasiński et al., 2018; Karabay et al., 2016; Tervonen, 2014; Tervonen, Figueira, et al., 2009; Tervonen, Linkov, et al., 2009)
	SMAA-FFS (SMAA + Fuzzy Flow Sort)					(Pelissari, Oliveira, et al., 2019)	(Gaganis et al., 2020; Pelissari et al., 2021; Pelissari et al., 2019)
THESEUS	THESEUS	Fuzzy numbers	Not necessary	Yes	Partial relative	(Fernandez & Navarro, 2011)	(Fernandez et al., 2014, 2017; Navarro et al., 2013)
TODIM and FSE	TODIM-FSE	Deterministic	Yes (contribution function)	No	Partial relative (Prospect Theory's value function)	(Passos & Gomes, 2014)	(Araújo, 2015; Passos et al., 2014)
TOPSIS	TOPSIS SORT	Deterministic	Yes	Yes	Pairwise (ideal solution)	(Sabokbar et al., 2016)	(Gül, 2021; Silva et al., 2020; Silva & Almeida Filho, 2020; Yamagishi & Ocampo, 2021)
	TOPSIS SORT-B					(Silva & Almeida Filho, 2020)	Not found
	TOPSIS SORT-C					(Silva & Almeida Filho, 2020)	Not found
UTA	UTADIS (I, II and III)	Deterministic	Yes	Yes	Preference disaggregation of decision maker's overall preference	(Devaud et al., 1980)	(Asl et al., 2021; Esmaelian et al., 2016, 2017; Manshadi et al., 2015; Mehregan et al., 2018; Asl et al., 2021; Yang & Jiang, 2020; Zopounidis & Doumpos, 1999)
VIKOR	VIKOR SORT	Deterministic	Not necessary	Yes	Pairwise (ideal solution)	(Demir et al., 2018)	Not found

As shown in Table 1, CPP TRI differs from other methods with a similar purpose. In fact, the preference for a specific method depends on the nature of the problem, the format of data, calculation complexity, among other features. In the literature, two methods explore probability densities to deal with uncertain data in sorting problems, defining class acceptability indices with SMAA-Tri, or expressing the percentage that an alternative belong to each class, as CPP TRI (Ishizaka, Tasiou, et al., 2020). Although both methods favor a probabilistic approach to assessments, SMAA is more complex than CPP. SMAA requires Monte Carlo iterations and, for having practical applicability, the complexity of SMAA computations should not be too high with respect to the number of criteria and alternatives (Tervonen & Figueira, 2008). CPP calculation procedures in R and Matlab softwares indicate reduced processing time, without the need to implement Monte Carlo simulations, nor requires any rate between the number of criteria and alternatives (Casado & Silva, 2017; Gavião et al., 2018; Sant'Anna et al., 2012). Therefore, this paper explores CPP TRI with an application to the Caviar Project, introducing an interesting variant to refine elements that belong to a certain class.

4 MATERIALS AND METHODS

The methodology explored here involved five steps, illustrated by Fig. 1. The 1st step consisted of data collection. In social network analysis, data are organized in a square matrix called "adjacency matrix". The rows and columns of this matrix are composed of network actors and the internal values correspond to the measures of the links considered in the problem. The 2nd step focused on the centrality algorithms available in the "CINNA" package of the R software (Ashtiani, 2019). This package provides several functions for calculating, comparing and demonstrating the main measures of centrality in a network. In the 3rd step, Principal Component Analysis (PCA) was used to reduce the problem dimension, by selecting the most representative centrality measures, through a function of the "CINNA" package, called "pca_centralities" (Ashtiani, 2019). The 4th step elaborated a decision matrix with the network nodes as alternatives (matrix rows), the main centralities indicated by PCA as criteria (matrix columns) and the respective measures of centrality as the evaluations of the alternatives by each criterion. The 5th step consisted of the application of CPP-TRI, admitting different scenarios of class profiles.

The classification of alternatives by CPP-TRI requires prior definition of representative profiles for each class chosen. A profile is a vector with one coordinate for each criterion used as a reference to classify an alternative at different levels of quality. These levels can define, for example, a high and a low performance class. The profiles of classes can be established based on a priori information about the context, by expert opinion, by measures of statistical position, among other possibilities (Sant'Anna, 2015). Fig. 2 illustrates the marking of class profiles for two categories. In the present study, the profiles are chosen based on percentiles of performance according to each criterion. The dotted line indicates each profile.

The classification algorithm of the 5th Step is based on Equations (1) to (6). The randomization of assessments is the first step of CPP. Exact measures of performance are interpreted as location parameters e.g. mean, mode, or median) of a statistical distribution. The choice of the proba-

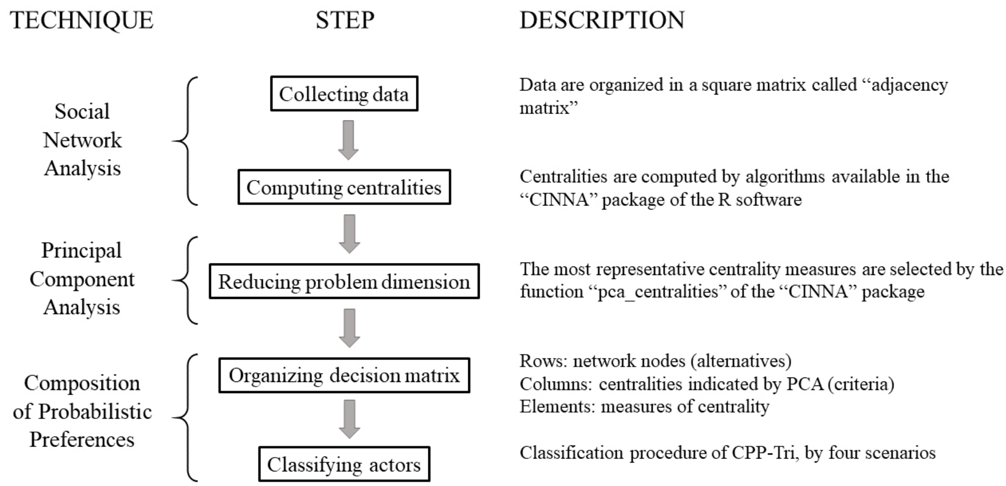

Figure 1 – Research design.

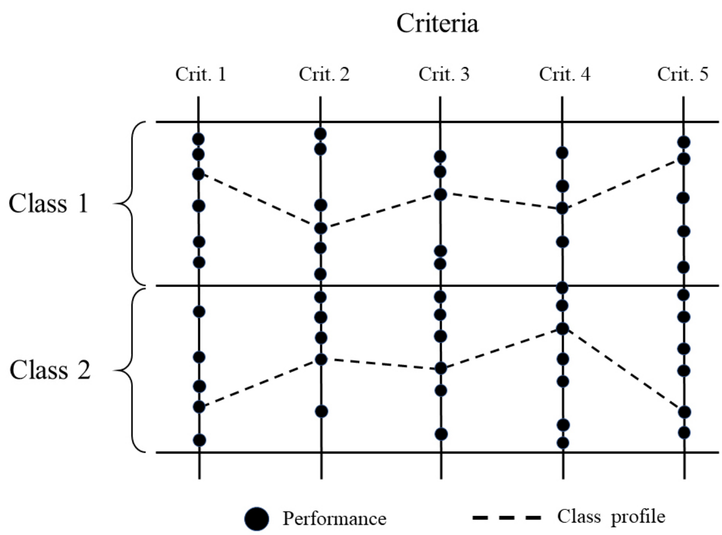

Figure 2 – Performance and class profiles.

bilistic distribution that best fits the data is usually based on a priori information, on successful experiences in similar problems or from a goodness-of-fit function. In the absence of such information, it is still possible to use an empirical approach or even arbitrate a probability distribution according to the context.

Fig. 3 illustrates a generic randomization of an exact performance evaluation $a_{kj} = 7$, by a Beta PERT distribution, with minimum, mode and maximum parameters equal to 0, 7, and 10, respectively, and shape equal to 10. This procedure of randomization is performed for each a_{kj}

element of the decision matrix. This transformation of an exact number into a probability distribution takes into account the uncertainty of data collection, recording processes and preference decisions in the intelligence realm.

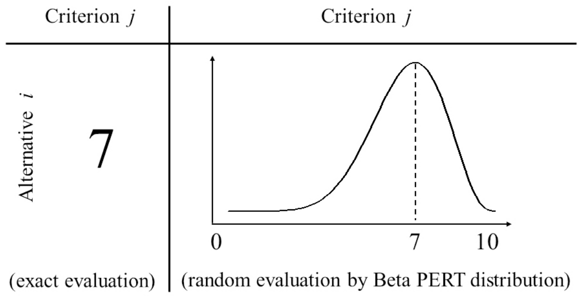

Figure 3 – Generic randomization.

After the randomization, in a multiplicative composition with one representative profile per class (Sant'Anna et al., 2012), for i denoting the class, j denoting the criterion, c_{ij} denoting the j-th coordinate of the representative profile of class i and X_{kj} denoting the random variable derived from the numerical assessment of the k-th alternative by the j-th criterion, the classification procedures starts with the computation of the probabilities. Notations A^+ and A^- indicate the probabilities of alternative A being respectively above and below the values reported for the j-th criterion in the i-th class profiles.

$$A_{ijk}^{-} = P[X_{jk} < C_{ij}] \tag{1}$$

$$A_{ijk}^{+} = P[X_{jk} > C_{ij}] \tag{2}$$

Then, estimates of joint probabilities of each alternative being below and above each class are computed:

$$A_{jk}^{-} = \Pi_i A_{ijk}^{-} \tag{3}$$

$$A_{jk}^{+} = \Pi_i A_{ijk}^{+} \tag{4}$$

The classification is completed with the computation of the distances (Δ).

$$\delta_{ik} = |A_{jk}^{+} - A_{jk}^{-}| \tag{5}$$

The k-th alternative is classified in a class i_0.

$$\delta_{i_0 k} = min_i \delta_{ik} \tag{6}$$

The algorithms for classifying alternatives in CPP-TRI are available in the "CPP" package of software R (Gavião et al., 2018). Fig. 4 illustrates the allocation of an alternative to its most appropriate class, considering one alternative ("A") and two classes.

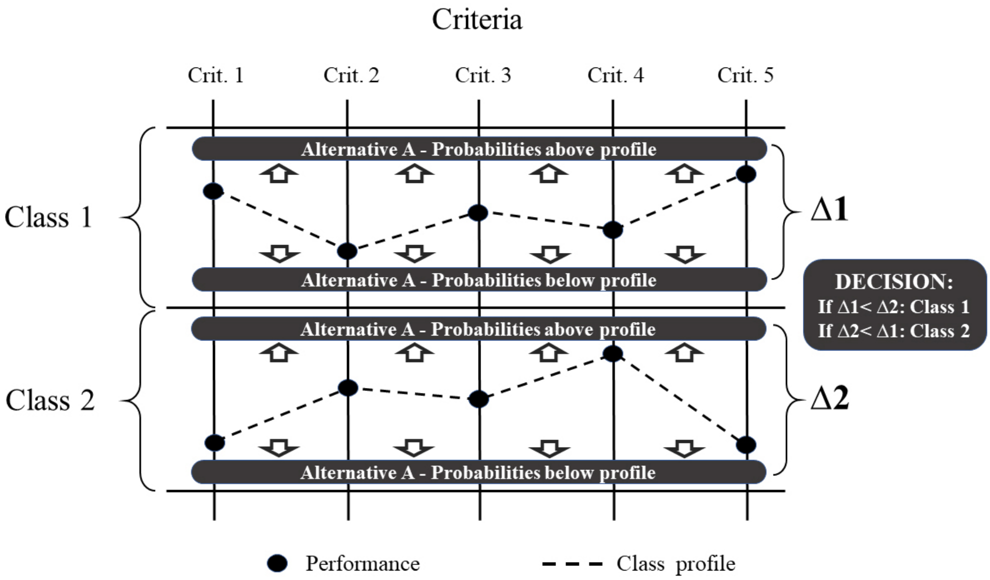

Figure 4 – Classification procedure of CPP-TRI.

5 REVISITING THE CAVIAR PROJECT

The Caviar Project was an anti-drug investigation based on the analysis of social networks (Morselli, 2009). Investigations have raised a hash and cocaine trafficking network operating outside the city of Montreal, Canada. The network was monitored between 1994 and 1996 by officers from the Montreal Police, the Canadian Mounted Police and other national and international police parties.

This investigation was peculiar because the agents seized shipments of drugs without detaining the participants. This atypical context of police intervention was used to observe and analyze the behavior of the actors during the investigation. Thus, although 11 shipments were seized at different times during the investigations, the arrests occurred only at the end of the investigation.

The main source of data was composed of information collected from telephone conversations between network participants, which were intercepted electronically. More than a thousand pages of transcripts were recorded and analyzed to create an adjacency matrix based on the connections between members of the drug trafficking network.

Initially the intercepted data allowed identifying 318 individuals. However, several of them were not involved in trafficking operations and others did not reveal a clear participatory role in the network, among which are family members or legitimate entrepreneurs. With the removal of members with no relevance to the drug trafficking network, the final list of investigated individuals was composed of 110 actors, represented in the following description arbitrarily by integers from “1” to “110”. From this group of 110 actors, 25 were arrested, 22 accused and 14 considered guilty.

The adjacency matrix in Table 2 presents a sample of the collected data from the UCINET software base (Coutinho, 2016), which provides open access to the Caviar network data in a “.csv” file. This matrix is also presented in (Morselli, 2009). The full matrix of 110 actors is found in the Appendix. The values of the matrix elements describe the exchanges of communication between drug traffickers, originating from the police wiretapping. These measures represent the level of communication activity. For example, Criminal #3 made 152 calls to Criminal #1, while Criminal #1 made 337 calls to Criminal #3. This characterizes the weighted directionality of the network. It is also possible to verify that the main diagonal of the adjacency matrix is null, since an actor does not make calls for himself.

Table 2 – Adjacency matrix (sample).

Criminals	1	2	83	3	85	82	88	89	4
1	0	52	81	337	142	73	9	30	10
2	29	0	0	3	0	0	0	0	0
83	6	0	0	1	0	0	0	0	0
3	152	1	5	0	29	2	2	2	0
85	33	0	0	18	0	0	12	0	0
82	18	0	0	2	0	0	0	0	0
88	2	0	0	1	10	0	0	0	0
89	2	0	0	1	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0

Source: adapted from (Coutinho, 2016).

Based on the entire adjacency matrix, the centralities of the network actors were calculated. The CINNA application returned results for 37 types of centralities. Then, PCA was used to select the most representative types of centrality. Fig. 5 graphically describes the results of PCA, a cut-off line separating the more and less representative types. The cut-off line reflects the intensity that must be exceeded in cumulative percentage of variance of eigenvalues, being adopted the default=80, suggested in CINNA. Therefore, only 10 criteria were kept in the process.

Table 3 presents a sample of the results of the PCA, as shown in Fig. 5. The full matrix of 110 actors is also found in the Appendix. Those results configure the decision matrix to be modeled with CPP TRI. The ten most representative criteria, in order of relevance from highest to lowest contribution to results, are indicated in the columns: (C1) Local Bridging Centrality; (C2) Information Centrality; (C3) EPC - Edge Percolated Component; (C4) Harary Centrality;

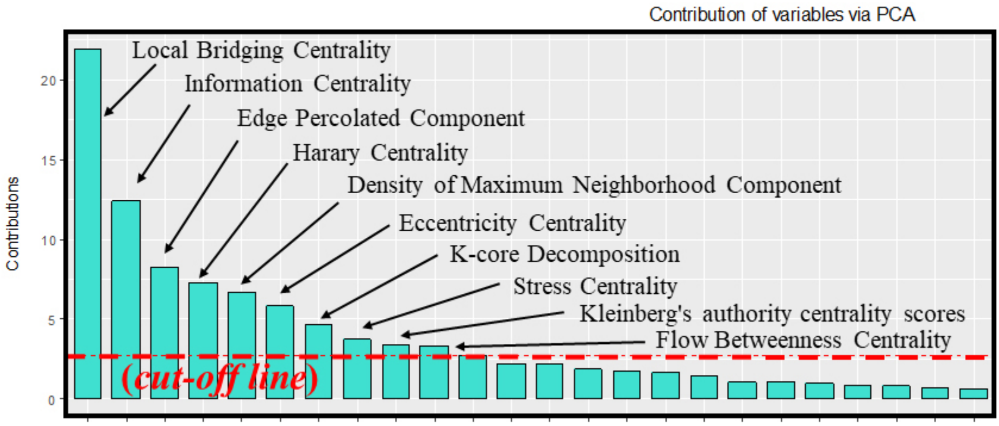

Figure 5 – The most representative types of centrality.

(C5) DMNC - Density of Maximum Neighborhood Component; (C6) Eccentricity Centrality; (C7) K-core Decomposition; (C8) Stress Centrality; (C9) Kleinberg's authority centrality scores; and (C10) Flow Betweenness Centrality. The specifics of these centrality measures and general PCA procedures are detailed in the "CINNA" package of software R (Ashtiani, 2019).

Table 3 – Centrality results after PCA (sample of criminals).

Criminals / Centralities	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	0.0003	1.3438	755.9455	0.3333	0.3901	3	6	6643	0.0757	3689
2	0.1194	0.5794	751.4455	0.25	0.9876	4	5	0	0.1525	0
83	0.0435	0.5794	755.9455	0.25	0.9032	3	6	0	0.2391	0
3	0.0037	0.6231	755.9455	0.2	0.4814	3	6	0	1.0000	41
85	0.2280	0.7065	753.6818	0.2	0.9525	4	6	1	0.4237	70
82	0.0407	0.5855	753.7727	0.25	0.6021	4	6	0	0.2185	0
88	0.1259	0.3718	752.9091	0.2	0.9876	4	6	0	0.0285	0
89	0.0280	0.8985	753.8091	0.25	0.9525	4	6	0	0.0884	0
4	2.0222	0.5794	662.2455	0.25	0.6285	4	3	0	0.0293	0

Finally, the application of CPP TRI to this decision matrix concludes the modeling leading to the results in Table 4. Two classes (1 and 2) were designated to represent the actors with the greatest and least relevance in the network. This identification is important during investigations to raise the most influential actors in the drug trafficking network. Four scenarios were established in which each class is represented by a single profile. The class profiles are constituted by statistic percentiles of the data for each criterion, indicated in parentheses in the heading of Table 4. The increase of 5% in the profiles gives greater selectivity for the classification of the actors. For example, it is possible to verify that Criminal #1 remained in the most important class in the four scenarios, while Criminal #3 remained slightly below Criminal #1 because he was reclassified in the most restrictive scenario (profiles 90% and 65%). The probability distributions were modeled with the "*CPP.Tri.Beta*" function, available in the "CPP" package of software R (Gavião et al., 2018).

Initially, Criminals #1, #3, #12, #76 and #87 were highlighted for analysis. The Caviar Project priorized those criminals due to results of the network analysis with degree and betweeness centrality measures (Morselli, 2009). Although these two centralities are among the most explored in social networks analyses, the use of ten most representative measures among 37 types of centralities allowed identifying in greater depth the real importance of these actors in the criminal network. Of these five actors, only Criminal #1 and, in a way, Criminal #3 were confirmed the most important in the modeling here explored. Criminals #12 and #76 were classified in the least relevant class in all scenarios, while Criminal #87 obtained an intermediate result between classes 1 and 2.

Further analysis is needed about the Criminal #12. Morselli & Petit (2007) identified #1 and #12 as among the most important players in the network. They computed centrality scores for the overall Caviar network to indicate the extent to which Criminals #1, #3 and #12 were positioned as key participants. Criminal #1 was the most central participant (degree centrality = 55; betweenness centrality = 64), followed by Criminal #3 who was equally connected (degree centrality = 25), yet less indirectly connected (betweenness centrality = 11) in his communications than Criminal #12 (degree centrality = 25; betweenness centrality = 29). They also describe Criminal #12 as "the principal coordinator for the cocaine consignments" and therefore logically among the top law enforcement targets.

However, the results regarding criminal #12 in the proposed modeling did not reach the class with the greatest attention to law enforcement. This does not mean to say that it is irrelevant to the investigations, but in the set of several centrality measures, Criminal #12 did not performed in the same way. The mathematical model is just a complement that contributes to fragment the network, indicating other actors that deserve investigation to confirm or not its relevance in the network. It is reasonable to assume, for example, that the connections with a given head of the network are protected and generate less data in a adjacency matrix. In summary, quantitative analysis goes hand-in-hand with qualitative analysis by experts in criminal investigations, so that the puzzle of a criminal organization can be effectively put together.

In Table 4, the criminals under gray-shaded lines are also selected for analysis. The results indicated that Criminals #8, #22 and #59 are at the same level as Criminal #1, while Criminals #9, #14, #78, #89 and #106 are at the same level as Criminal #3. In practice, these results would indicate the use of additional resources and special attention to a wider range of actors during the two years of investigation. For some reason, Criminals #8, #22 and #59 have connections as relevant as those of Criminal #1. The same observation applies to criminals at Criminal #3 level.

Table 4 – CPP TRI results.

	Scenarios (profiles in %)			
Criminals	(75%-50%)	(80%-55%)	(85%-60%)	(90%-65%)
1	1	1	1	1
2	1	2	2	2
3	1	1	1	2
4	2	2	2	2
5	1	1	2	2
6	1	2	2	2
7	2	2	2	2
8	1	1	1	1
9	1	1	1	2
10	1	2	2	2
11	1	2	2	2
12	2	2	2	2
13	1	1	2	2
14	1	1	1	2
15	1	2	2	2
16	2	2	2	2
17	2	2	2	2
18	2	2	2	2
19	2	2	2	2
20	2	2	2	2
21	2	2	2	2
22	1	1	1	1
23	2	2	2	2
24	1	2	2	2
25	2	2	2	2
26	2	2	2	2
27	1	1	2	2
28	2	2	2	2
29	1	1	2	2
30	2	2	2	2
31	2	2	2	2
32	2	2	2	2
33	2	2	2	2
34	2	2	2	2
35	2	2	2	2
36	2	2	2	2
37	2	2	2	2

	Scenarios (profiles in %)			
Criminals	(75%-50%)	(80%-55%)	(85%-60%)	(90%-65%)
56	2	2	2	2
57	2	2	2	2
58	2	2	2	2
59	1	1	1	1
60	2	2	2	2
61	2	2	2	2
62	1	2	2	2
63	2	2	2	2
64	1	1	2	2
65	2	2	2	2
66	2	2	2	2
67	2	2	2	2
68	2	2	2	2
69	2	2	2	2
70	2	2	2	2
71	2	2	2	2
72	2	2	2	2
73	2	2	2	2
74	2	2	2	2
75	2	2	2	2
76	2	2	2	2
77	2	2	2	2
78	1	1	1	2
79	2	2	2	2
80	1	2	2	2
81	2	2	2	2
82	1	1	2	2
83	1	2	2	2
84	2	2	2	2
85	1	1	2	2
86	2	2	2	2
87	1	1	2	2
88	2	2	2	2
89	1	1	1	2
90	2	2	2	2
91	2	2	2	2
92	2	2	2	2

Continued on next page

	Scenarios (profiles in %)			
Criminals	(75%-50%)	(80%-55%)	(85%-60%)	(90%-65%)
38	2	2	2	2
39	2	2	2	2
40	2	2	2	2
41	1	2	2	2
42	2	2	2	2
43	2	2	2	2
44	2	2	2	2
45	2	2	2	2
46	1	1	2	2
47	2	2	2	2
48	2	2	2	2
49	1	2	2	2
50	2	2	2	2
51	2	2	2	2
52	2	2	2	2
53	2	2	2	2
54	2	2	2	2
55	2	2	2	2

	Scenarios (profiles in %)			
Criminals	(75%-50%)	(80%-55%)	(85%-60%)	(90%-65%)
93	1	2	2	2
94	2	2	2	2
95	2	2	2	2
96	1	2	2	2
97	2	2	2	2
98	2	2	2	2
99	2	2	2	2
100	2	2	2	2
101	2	2	2	2
102	1	2	2	2
103	2	2	2	2
104	2	2	2	2
105	2	2	2	2
106	1	1	1	2
107	2	2	2	2
108	2	2	2	2
109	1	2	2	2
110	2	2	2	2

Fig. 6 complements and illustrates the information presented in Table 4. We see the bands indicating the four scenarios and the actors highlighted in Table 4. In hollow circles are the criminals analyzed in the original study. In full circles the new actors identified in this research. It is also possible to identify the changing of profiles in each scenario, like obstacle barriers, which rise and become more restrictive to classify the actors. As the bar rises, some criminals retain their main class and others are relocated to class 2.

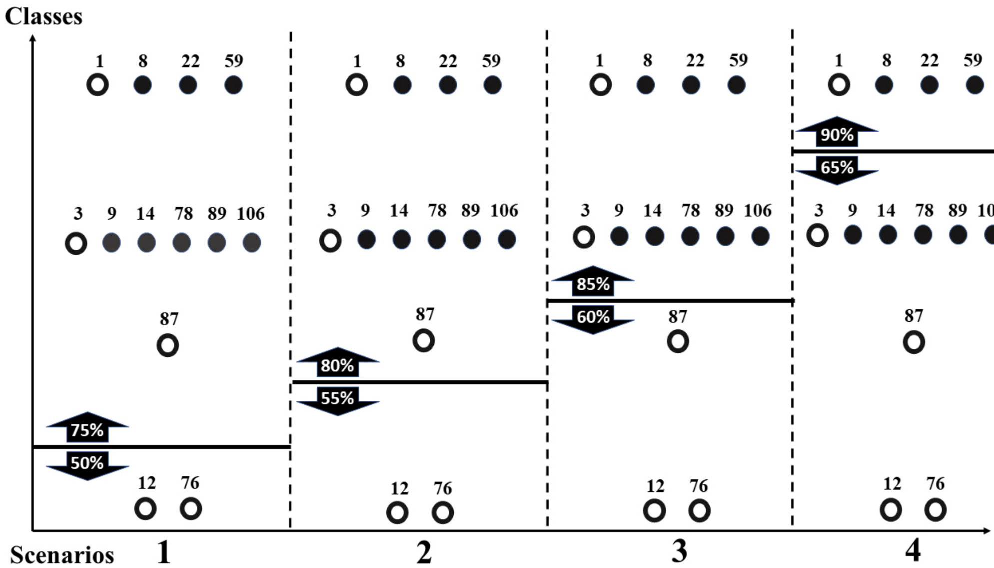

Figure 6 – Illustration of Table 4 results.

The study continued with additional calculations on the groups indicated in Table 5. Even if they are classified as highly relevant actors in the network, it is possible that their criminal activities are organized and divided by similar tasks, by geographic location or by any other procedure that allows grouping them in clusters. The numbers indicated in the matrix discriminate clusters that join or separate sets of actors, for each technique used. The clustering analysis of the adjacency matrix was performed using the application "*igraph*" package, from software R (Csardi & Nepusz, 2006).

Table 5 shows the results of six clustering techniques for social networks, applied to the criminals highlighted in Table 3. Details of the calculation procedures for these techniques are available in the "*igraph*" package (Csardi & Nepusz, 2006). Note that the numerical results in Table 5 do not order the groups, they only discriminate against them. The results indicate that Criminals #1, #8, #3, #106 and, probably #9 and #89, belong to the same functional group in the criminal network. By different techniques, these actors remained in the same group, indicated by the result "1". It can also be seen that Criminals #22 and #14 coincide in five of the six techniques, and they are also likely to act in the same tasks, they are geographically close or even have some kind of special connection. Criminals #59 and #78 coincided in four of the six techniques

Table 5 – Clustering criminals.

Criminals	*Cluster optimal*	*Cluster edge betweenness*	*Cluster infomap*	*Cluster label prop*	*Cluster leading eigen*	*Cluster louvain*
1	1	1	1	1	1	1
8	1	1	1	1	1	1
22	4	3	2	2	4	4
59	5	1	6	2	4	2
3	1	1	1	1	1	1
9	1	3	1	1	1	1
14	4	1	2	2	4	4
78	5	1	1	1	4	2
89	3	1	7	1	1	1
106	1	1	1	1	1	1

and, likewise, may have some type of activity in common in the criminal network. Finally, note that mathematical results are useful indicators for law enforcement officers to intensify their investigative work with priority for certain actors. This prioritization can be decisive in criminal networks composed of a high number of actors and links, as it reduces uncertainty, optimizes the use of investigation resources, and brings the focus to the most relevant actors in the network.

The main source consulted about the Caviar Project indicates that 14 criminals were found guilty in the network. However, the 110 actors "*numbered*" in Morselli (2009) are neither associated with their names nor with their penalties. This lack of information does not allow a direct comparison between results from different approaches. Despite that, two advantages of the methodological proposal are visualized. First, the use of a large amount of centrality measures, submitted to PCA to select the most relevant ones, improves the accuracy and quality of criminal identification, because it goes beyond the use of only two centrality measures used in the original research. Second, after computing the centrality measures, the use of a multicriteria decision aid method to select the most important criminals in the network is a natural step. Thus, this new approach highlighted new actors with important participation in the network.

6 CONCLUSION

The analysis of social networks based on measures of centrality is a useful tool to support researchers in problems in criminology. The analysis of social networks is based on graph theory, which presents several types of centrality measures to evaluate the influence of the nodes of a network, based on the quantification of its links. In the specific case of the Caviar network, the nodes were associated with the actors and links were measured based on wiretapping, whose unit of measure was represented by the number of directional calls from actor "x" to actor "y". These links were then consolidated into a square matrix, called the adjacency matrix, which sets up the initial database for the analysis of social networks.

In this study, a multicriteria decision support methodology was used to classify the main actors in the criminal network, which operated in the drug trade in Canada. CPP TRI is a variant of CPP, being used for the ordered classification of alternatives. The results of the Caviar network investigations were compared and ratified with the results of application of the methodology proposed.

The article also contributed to a new approach to the application of CPP to support decision making in criminology. Graph theory and social network analysis can be enhanced with the use of MCDA methods, what is confirmed by the publication of studies in this regard. CPP, in particular, has interesting variants to bring new perspectives to investigators, identifying actors who may have remained hidden with the use of few measures of centrality. The methodological procedure that associates PCA to CPP TRI and the use of scenarios with different class profiles also proved to be relevant, as it allowed selecting the actors through progressive restrictions, with reduced computational effort. This methodological procedure becomes even more important if criminal networks have large numbers of actors. The Caviar network was composed of 110 actors, but criminal networks can contain thousands of actors, which must be classified, for the optimization and prioritization of limited investigative resources.

New research can deepen the study presented here. Initially, the possibility of including new CPP variants is imagined. It is possible, for example, to analyze the dynamic evolution of the centrality measures with Malmquist indexes. CPP has applications in this context and the assessment of investigations in stages may receive the application of the method. The possibility of performing CPP TRI tests with network dimensions of the order of thousands of components is also visualized to verify the computational performance of the R software. For the time being, the biggest limitation for this type of test is in the accessibility to real data with matrices of adjacent networks of such dimensions, due to the need of preserving data confidentiality.

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Table 6 – Adjacency matrix (110 actors).

Crim.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	0	52	337	10	49	25	1	46	39	6	12	11	11	3	11	0	0	0	21	7	0	0	0	0	0	0	0	3	0	0	0	0	0	4	1	0	2
2	29	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0
3	152	1	0	0	0	0	1	21	16	0	0	21	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0
4	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	65	0	3	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	41	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	10	0	1	0	1	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
9	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	118	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	0	25	0	0	0	0	0	2	0	0	0	4	73	0	51	12	17	0	0	0	6	1	1	2	2	2	0	3	1	3	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	1	0	0	0	0	0	0	1	0	0	0	64	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
15	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	96	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	2	10	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	12
42	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
49	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
68	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
69	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
76	66	0	6	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
77	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
79	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
82	18	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0
83	6	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
84	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
85	33	0	18	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
86	5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
87	48	0	28	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	29
88	2	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
89	2	0	1	0	0	0	7	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
90	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
96	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
98	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
100	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
105	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
108	4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
109	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7 – Adjacency matrix (110 actors) (continuation).

Crim.	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74
1	0	0	0	2	0	0	0	0	0	2	2	3	2	1	4	0	2	9	1	2	0	0	0	0	1	0	6	0	0	1	0	0	4	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
13	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	46	4	1	22	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	4	0	0	0	0	0	0	0	0	0	1	2	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
79	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
85	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
86	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
87	2	9	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74
95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
96	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
105	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
109	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 8 – Adjacency matrix (110 actors) (continuation).

Crim.	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110
1	0	88	28	0	0	0	7	73	81	4	142	35	68	9	30	7	0	0	0	0	0	1	1	1	1	0	0	0	1	0	1	1	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	25	3	0	0	0	0	2	5	0	29	4	18	2	2	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	1	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	11	0	0	0	0	12	0	0	0	0	0	31	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	3	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
59	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
60	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
61	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	12	4	0	0	0	1	0	7	0	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0	27	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
79	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
81	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
82	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
83	0	0	0	0	0	0	0	0	0	5	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
84	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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Crim.	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110
85	0	9	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
86	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0
87	0	2	0	0	0	0	21	18	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0
88	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
96	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
97	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
101	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
102	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
104	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
105	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
109	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 9 – Centrality measures after PCA (110 actors).

Crim.	C1 - Local Bridging Centrality	C2 - Information Centrality	C3 - EPC - Edge Percolated Component	C4 - Harary Centrality	C5 - DMNC (Density of Maximum Neighborhood Component)	C6 - Eccentricity Centrality	C7 - K-core Decomposition	C8 - Stress Centrality	C9 - Kleinberg's authority centrality scores	C10 - Flow Betweenness Centrality
1	0,000344771	1,343776589	755,9454545	0,3333333	0,39013876	3	6	6643	0,075736501	3689
2	0,119394547	0,579377799	751,4454545	0,25	0,98755164	4	5	0	0,152472126	0
3	0,003744505	0,623125763	755,9454545	0,2	0,481363909	3	6	0	1	41
4	2,022222222	0,579377799	662,2454545	0,25	0,628506687	4	3	0	0,029274366	0
5	0,212785069	0,74837092	749,9181818	0,25	0,952463032	4	5	270	0,143492054	77
6	0,297899097	0,90419078	709,8727273	0,25	0,638656734	4	4	0	0,073251495	42
7	1,237342472	0,53732426	721,5181818	0,2	0,638656734	4	4	0	0,003222771	0
8	0,062104411	1,265064762	755,1636364	0,25	0,952463032	4	6	4589	0,140171616	2448
9	0,162478257	1,058824773	751,6545455	0,25	0,903150064	4	6	112	0,118725999	74
10	91	1,109829743	378,6272727	0,25	0	4	1	439	0,017564619	376

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Crim.	C1 - Local Bridging Centrality	C2 - Information Centrality	C3 - EPC - Edge Percolated Component	C4 - Harary Centrality	C5 - DMNC (Density of Maximum Neighborhood Component)	C6 - Eccentricity Centrality	C7 - K-core Decomposition	C8 - Stress Centrality	C9 - Kleinberg's authority centrality scores	C10 - Flow Betweenness Centrality
11	0,843545105	0,936722674	707,4272727	0,25	0,638656734	4	4	0	0,035129239	5
12	0,00153305	0,726830662	755,9454545	0,2	0,620592119	4	6	28	0,041353201	48
13	0,301574151	0,995640252	741,4090909	0,25	0,638656734	4	5	12	0,032870812	53
14	0,072112643	1,018888086	754,4818182	0,25	0,952463032	4	6	14	0,020722869	124
15	2,839781809	0,885576591	721,1818182	0,25	0,638656734	4	4	3	0,032201802	38
16	1,12	0,767693144	646,9090909	0,2	2	5	3	0	0,008110117	0
17	0,608695652	0,564241251	623,8818182	0,2	2	5	2	0	0,001908263	0
18	10,5	0,564241251	565,1545455	0,2	0	5	2	0	0,002703372	0
19	0,438941176	0,564241251	746,3272727	0,2	0,98755164	4	5	0	0,061920701	0
20	0,652589641	0,993353002	701,7272727	0,2	0,638656734	4	4	96	0,021495159	22
21	2,967741935	0,564241251	590,8	0,2	2	5	2	0	0,001949071	0
22	10,5	1,298797294	585,6909091	0,3333333	0	5	2	2167	0,000954131	846
23	10,5	0,99968494	568,6363636	0,25	0	5	2	66	0,000159022	26
24	0,548693587	0,814541294	712,2818182	0,25	0,638656734	5	3	0	0,000194031	0
25	10,5	0,564241251	561,7	0,2	0	5	2	0	0,000318044	0
26	42	0,776856376	363,3636364	0,25	0	5	1	0	0,000318044	41
27	0,917088608	0,905596047	727,0181818	0,25	0,638656734	5	5	0	0,000667028	0
28	91	0,520130042	387,9181818	0,2	0	4	1	0	0,00878231	0
29	10,5	1,115249605	585,3454545	0,25	0	5	2	1175	0,000477066	728
30	1,4	0,553366235	526,2454545	0,2	0,628506687	5	2	0	0,000167786	0
31	0,838364167	0,553366235	709,1727273	0,2	0,638656734	4	4	0	0,003162357	0
32	14,36842105	0,779034026	570,4090909	0,25	0,628506687	4	2	0	0	15
33	42	0,553366235	376,2545455	0,2	0	5	1	0	0	0
34	0,919191919	0,905689239	697,5545455	0,2	0,628506687	4	4	48	0,011771217	18
35	1,519832985	0,756397205	658,7818182	0,2	0,638656734	4	3	0	0,002973842	1
36	12	0,532345742	376,5090909	0,2	0	5	1	0	0,000194678	0
37	0,0110336	0,690940786	754,5636364	0,2	0,638656734	4	5	0	0,012072279	51
38	5,75	0,579377799	558,4636364	0,25	0	5	2	0	0,00042608	0
39	23	0,579377799	388,6363636	0,25	0	5	1	0	0,001917358	0
40	23	1,031794195	392,4	0,25	0	5	1	7	0,00021304	89
41	0,01836499	0,579377799	755,2545455	0,25	0,806887653	4	5	0	0,008338327	0
42	2,210526316	0,929155223	662,5	0,25	0	5	3	0	0,000126276	7
43	1,826086957	0,579377799	667,1363636	0,25	0,628506687	5	3	0	3,07633E-05	0
44	4,5	0,579377799	566,3	0,25	0	5	2	0	0,000676792	0

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Crim.	C1 - Local Bridging Centrality	C2 - Information Centrality	C3 - EPC - Edge Percolated Component	C4 - Harary Centrality	C5 - DMNC (Density of Maximum Neighborhood Component)	C6 - Eccentricity Centrality	C7 - K-core Decomposition	C8 - Stress Centrality	C9 - Kleinberg's authority centrality scores	C10 - Flow Betweenness Centrality
45	4,5	0,798621263	573,8181818	0,2	0	5	2	3	0,00018458	76
46	0,5	0,969200319	691,1909091	0,25	0,628506687	5	4	3	0,000682173	66
47	22,75	0,554639243	567,1363636	0,25	0	4	2	0	0,005854873	0
48	91	0,431396342	397,5090909	0,2	0	4	1	0	0,005854873	0
49	0,853233388	0,579377799	733,7818182	0,25	0,98755164	4	5	0	0,00878231	0
50	22,75	0,564241251	555,9818182	0,2	0	4	2	0	0,005854873	0
51	2,078406796	0,564241251	674,0454545	0,2	0,628506687	4	3	0	0,002927437	0
52	0,685240964	0,579377799	701,8636364	0,25	0,638656734	4	4	0	0,011791886	0
53	91	0,579377799	383,5363636	0,25	0	4	1	0	0	0
54	22,75	0,930169696	565,3272727	0,25	0	4	2	0	0,005854873	9
55	91	0,579377799	389,2636364	0,25	0	4	1	0	0,026346929	0
56	91	0,554639243	403,1	0,25	0	4	1	0	0,002927437	0
57	91	0,553366235	400,1272727	0,2	0	4	1	0	0,005854873	0
58	0,326732673	0,564241251	689,1818182	0,2	0,628506687	5	3	0	0,000416909	0
59	0,528	1,217796029	682,7363636	0,3333333	0	4	3	1690	0,000438212	790
60	5	1,143167326	355,6	0,25	0	5	1	328	0	336
61	6	0,902180217	560,4636364	0,25	0	4	2	181	0,000350137	126
62	91	1,062950099	361,2181818	0,25	0	4	1	451	0,002927437	313
63	3	1,053198599	314,1636364	0,25	0	5	1	236	0	129
64	91	1,137325934	402,4272727	0,25	0	4	1	645	0,017564619	330
65	42	1,135976941	393,1545455	0,25	0	5	1	101	0	117
66	10,5	0,812277196	567,3818182	0,25	0	5	2	0	0,000318044	2
67	91	0,553366235	388,7818182	0,2	0	4	1	0	0,002927437	0
68	91	0,538602929	389,8272727	0,2	0	4	1	0	0	0
69	91	0,756397205	374,0909091	0,2	0	4	1	0	0	24
70	91	0,538602929	399,8909091	0,2	0	4	1	0	0,011709746	0
71	6	0,532345742	571,2727273	0,2	0	4	2	0	8,75343E-05	0
72	24	0,839058155	373,6909091	0,25	0	4	1	152	0,000175069	112
73	23	0,579377799	392,7	0,25	0	5	1	0	0,00042608	0
74	41	0,579377799	370,3454545	0,25	0	4	1	0	0,000732352	0
75	42	0,812277196	404,9636364	0,25	0	5	1	0	0	1
76	0,008482532	0,694947213	755,9454545	0,2	0,709544818	3	6	0	0,266713257	43
77	1,17351646	0,855944401	702,2	0,2	0,638656734	4	4	0	0,082700576	52
78	0,573913043	0,564241251	725	0,2	4	4	5	0	0,001068616	0

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Crim.	C1 - Local Bridging Centrality	C2 - Information Centrality	C3 - EPC - Edge Percolated Component	C4 - Harary Centrality	C5 - DMNC (Density of Maximum Neighborhood Component)	C6 - Eccentricity Centrality	C7 - K-core Decomposition	C8 - Stress Centrality	C9 - Kleinberg's authority centrality scores	C10 - Flow Betweenness Centrality
79	0,042166558	0,694947213	729,7363636	0,2	0,638656734	4	5	0	0,002702505	0
80	42	1,143069883	396,1	0,25	0	5	1	786	0	452
81	0,139735173	0,532345742	706,6909091	0,2	0,628506687	4	3	0	0,024977479	0
82	0,040717861	0,585546024	753,7727273	0,25	0,602100043	4	6	0	0,218509658	0
83	0,043509002	0,579377799	755,9454545	0,25	0,903150064	3	6	0	0,239121302	0
84	0,469677419	0,564241251	733,2090909	0,2	0,638656734	4	4	0	0,011828617	0
85	0,227955215	0,706463564	753,6818182	0,2	0,952463032	4	6	1	0,423705267	70
86	0,110236058	0,53732426	753,9363636	0,2	0,952463032	4	6	0	0,104047703	0
87	0,006156971	0,579377799	755,9454545	0,25	0,451575032	4	6	0	0,204194795	0
88	0,125883611	0,371798923	752,9090909	0,2	0,98755164	4	6	0	0,028451782	0
89	0,027991034	0,898495649	753,8090909	0,25	0,952463032	4	6	0	0,088424377	0
90	3,533143939	0,769598023	719,3727273	0,25	0,628506687	4	4	0	0,020736173	0
91	23	0,991257549	377,8818182	0,25	0	5	1	0	0,000639119	15
92	14	0,877468111	395,4909091	0,25	0	5	1	0	3,54498E-05	35
93	0,984375	0,579377799	713,8	0,25	0,628506687	5	4	0	0,00096333	0
94	14	0,579377799	403,2090909	0,25	0	5	1	0	3,22271E-05	0
95	18	0,579377799	406,5454545	0,25	0	5	1	0	0,000522976	0
96	0,242021277	0,796448223	739,9454545	0,25	0,638656734	4	4	0	0,003342997	60
97	91	0,478413007	397,4636364	0,2	0	4	1	0	0,002927437	0
98	22,75	0,579377799	568,1272727	0,25	0	4	2	0	0,002927437	0
99	5,576980568	0,579377799	638,3181818	0,25	0,628506687	4	3	0	0,003171554	0
100	91	0,554639243	360,2454545	0,25	0	4	1	0	0	0
101	0,771929825	0,570854041	635,0545455	0,25	0,628506687	5	3	0	5,06818E-07	0
102	0,326732673	0,914977038	673,4	0,25	0,638656734	5	3	3	1,01766E-06	23
103	0,494565217	0,888232224	385,8545455	0,25	2	4	1	97	0,002927453	167
104	2	0,95513404	180,8545455	0,25	0	5	1	893	0	698
105	1,309926148	0,564241251	652,6363636	0,2	0,638656734	4	3	0	0,003994997	0
106	91	1,112003477	370,7272727	0,3333333	0	4	1	489	0,002927437	330
107	0,28057554	0,877468111	566,3636364	0,25	0,628506687	4	2	0	0,000196861	46
108	2,369791667	1,059265868	552,2818182	0,25	0,628506687	4	2	19	0	55
109	12	1,211675786	402,0272727	0,25	0	5	1	1647	7,31668E-06	842
110	12	1,027589705	375,7909091	0,25	0	5	1	98	7,31668E-06	110

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