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Using social network analysis to study crime: Navigating the challenges of criminal justice records

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ABSTRACT

The use of social network analysis to study groups of offenders engaged in illicit activities such as drug trafficking and terrorism has grown in popularity over the last three decades. Along with such growth, however, researchers have been confronted with a suite of challenges related to the use of data extracted from criminal justice records. In this paper, we review these challenges through a discussion of the extant empirical literature utilizing social network analysis approaches that draw data from the criminal justice system. First, we outline and discuss the different types of data used across this literature. Second, we chronicle the challenges that have emerged across the field of criminal networks via a comprehensive review of the literature. In particular, we draw on the documented experiences of researchers in the field, including our own, and detail "archeological" approaches that future researchers can utilize to adapt and overcome said challenges. The use of criminal justice records can suffer from a number of limitations, mainly with respect to accuracy, validity and reliability. Such data may include errors, both intentional (e.g. aliases, false information) and unintentional (e.g. transcription errors), including missing data. The use of criminal justice records present particular problems with defining the network boundary as the boundary as determined by law enforcement or prosecution agencies may not correspond to the boundary as defined by network members. We conclude by offering a number of recommendations for researchers about data collection and preparation when utilizing criminal justice records.

Introduction

In his seminal text, *Outsiders*, Howard Becker (1963) noted that "the most persistent difficulty in the scientific study of deviant behavior is the lack of solid data" (p.165). This sentiment applies to all types of research on crime, criminals and criminal behavior. Crime is usually hidden and often undetected, and criminals tend to maintain social barriers between themselves and out-group members including researchers. Not to be deterred, innovative researchers have sought out novel sources of data and analytical approaches to provide more robust understandings of crime. In recent years, social network approaches that involve the collection of criminal justice records on actors and the links between them, have provided powerful new ways to study crime and understand criminal networks. Criminal justice records can yield unique insights into offence and offender characteristics that can permit the mapping of the diverse connections that exist between criminal actors. Social network analysis (SNA) can then be used to enhance understandings of how emergent social structures shape various criminal activities, and how crime can be controlled (Brewer, 2017; Morselli, 2009b). The use of social network analysis to study groups of offenders engaged in illicit activities such as drug trafficking and terrorism has grown in popularity over the last three decades. Indeed, in a recent article, Faust and Tita (2019) predict that the field has been evolving such that "network methods [will] become part of the standard toolkit in criminological research" (p. 117). Along with such growth, however, researchers have been confronted with a suite of challenges related to the extraction and use of data collected from criminal justice records. Such sources are varied and can be broadly categorized as follows: offender databases, investigative records, prosecution files, court files, reports of department inquiries and commissions, and the use of multiple sources (i.e.

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† Professor Carlo Morselli passed away in October 2020. Incredibly kind and generous, Carlo was a great supporter of, and valued mentor to many scholars in the field of crime networks. He will be greatly missed.

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triangulation).

In this paper, we explicate these challenges via a critical review of the literature, along with some reflections from our own research using criminal justice records. Along the way, we provide a detailed review of the extant empirical literature that utilizes data from the criminal justice system to undertake SNA. While this is not a formal systematic review, our discussion is based on a literature search protocol that adhered to strict search parameters (see protocol, below). This analysis demonstrates that the use of SNA to study crime encounters the very challenges described by Becker. The current paper identifies and critically examines some of the challenges associated with the use of criminal justice records, particularly with respect to its collection, analysis and interpretation. We argue that given the challenges and constraints facing researchers in this field, criminal network researchers must approach the field like archeologists (see Becker, 1963), gathering limited data and adapting their observations, analyses and interpretations accordingly.

This article proceeds in four parts. First, we outline our search protocol used to find SNA research which has utilized data from criminal justice records. Second, we identify and discuss the different types of data used across this literature and the analytical techniques made possible through such approaches. Third, we chronicle the challenges that have emerged across the field of criminal networks. In particular, we draw on the documented experiences of researchers in the field, including our own, and detail "archeological" approaches that future researchers can utilize to adapt to and overcome said challenges. This paper concludes by drawing together the key points emerging from the discussion and offers a number of recommendations for researching in the field – a way forward – which we hope will enhance consistency of research practice, equip seasoned researchers with a set of consistent approaches, provide neophyte researchers with a path to navigate a challenging terrain, and encourage new researchers to enter the field.

Search protocol

Fig. 1 presents a flow chart of the search and inclusion/exclusion processes used, including the number of articles located in the searches and the number included following implementation of inclusion criteria. We first compiled a list of empirical research studies through an exhaustive search of databases using pre-defined search terms. Databases included Google scholar, EBSCO, Informit, Hein Online, Oxford University Press Journals, Proquest, JSTOR, Sage Journals, Science Direct, Taylor & Francis Online, Web of Science, SpringerLink, and Wiley Online Library. Search terms used were: (*social network analysis* OR *SNA*) AND (*Crim** OR *devian** OR *illicit* OR *delinquen** OR *offend** OR *co-offend** OR *polic** OR *law enforcement* OR *security* OR *terror** OR *cybercrime**). Searches were conducted between 3–5 April 2019. Two phases of inclusion criteria were then applied (see Fig. 1). In phase 1, titles and abstracts were manually reviewed by members of the research team and included only if they met the following criteria: (1) the abstract mentioned crime (including co-offending and terrorism), and (2) the abstract mentioned networks. Duplicate articles were excluded. In phase 2, articles were excluded if they did not adhere to the following selection criteria: (1) the research needed to be published in peer-

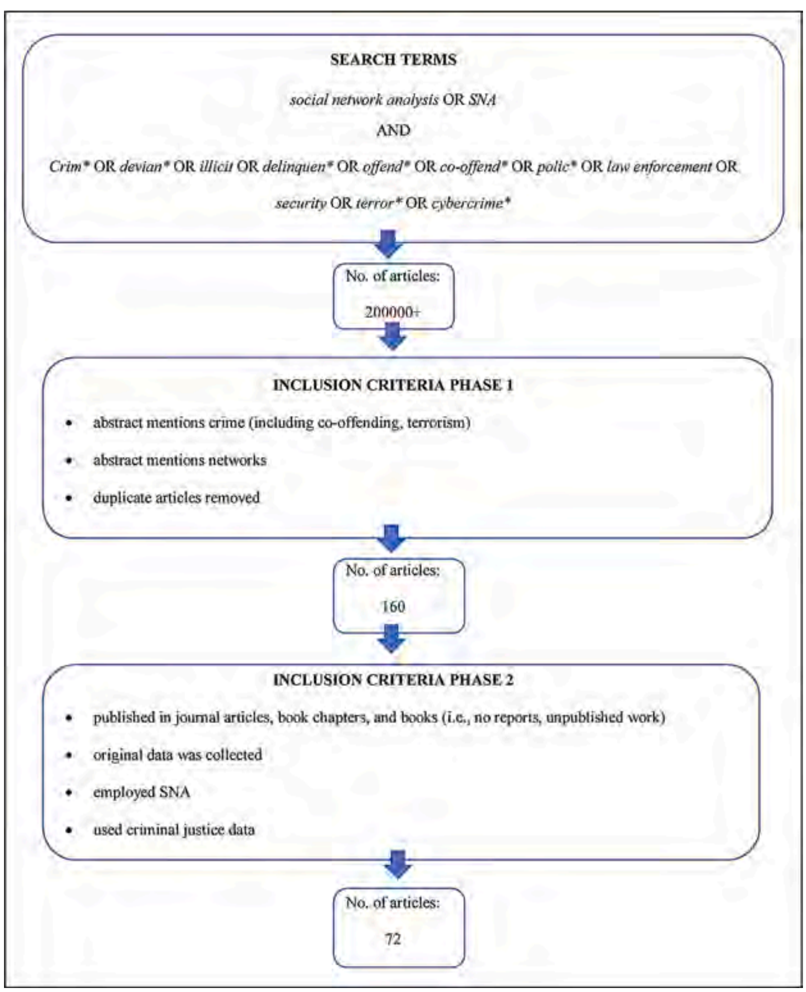

Fig. 1. Database search keywords, inclusion criteria and results.

reviewed journal articles, book chapters, and books (i.e. no reports, unpublished work). (2) the research needed to analyze criminal justice records obtained by the authors. (3) the analytical framework needed to incorporate social network analysis (i.e. reported social network analysis metrics such as centrality or presented a social network map comprised of actors and ties between them); (4), articles had to be available in print or online by 1st November 2018 to ensure it was indexed by the abovementioned databases at the time of searches. This two-phase process resulted in a total of 72 published works that utilized data sourced from the criminal justice system.

Criminal justice system data and social network analysis

Within the scope of the data gathering and fieldwork strategies that are more consistent with traditional social scientific methods, a large number of researchers have tapped into data sources that have previously been overlooked or dismissed. Such data sources fall under the wide scope of criminal justice data alternatives that criminologists have been using for over a century for the analysis of crime and criminal justice trends. As in other fields, network researchers within a criminological context found the same dyadic relationships that other researchers identified in their own adaptations of network analysis within sociology, anthropology, health, economics and other areas of research.

If there is one researcher who opened the field to criminal justice records, it is Sparrow (1991) who made an explicit call in a seminal *Social Networks* article in the early 1990s. In that paper, he outlined the incentives and opportunities that were facing researchers who were interested in expanding the social network analytical field into a new frontier. It took roughly a decade for Sparrow's call to gain momentum. The first steps were not easy. One of this paper's co-authors recalls his first presentations at Sunbelt conferences in which he presented his first studies on drug importation networks to a skeptical reaction by a good share of the audience who initially believed that he was working for the police. In the end, the critical stance brought to the data analysis gradually reassured most of the audience that there was something beyond the "who to arrest" analytical path.

To conduct social network research on criminal networks, researchers must collect at least two types of data: data on individuals who are deemed part of an criminal network or group and data on the relations or connections between those individuals (i.e. whether or not there is a tie or edge between every pair of actors). Various forms of criminal justice records have proved particularly fruitful for both types as well as having other benefits, such as having time stamps (i.e. permitting longitudinal analysis) or including information that facilitates coding of actor and tie attributes (i.e. demographics, roles, type/direction of a tie). The use of these sources of data for study using SNA is critically discussed below, based on our review of the existing literature. Table 1 lists the number of articles that collected data from the different data sources (a full list of articles is presented in Appendixes A–G).

Twenty studies utilized *investigative records*, with data sourced from files documenting police investigations including evidence collected/seized as part of investigation (e.g. wiretap transcripts, physical surveillance reports, seized computer hard drives). Such data was sourced from law enforcement agencies across North America and Europe (see Appendix A), and informed studies examining networks focusing on drug trafficking and manufacture (Duijn and Klerks, 2014; Framis, 2014; Framis and Regadera, 2017; Morselli and Giguere, 2006; Morselli and Petit, 2007; Morselli, 2009b; Natarajan, 2000, 2006), terrorist activity (Mainas, 2012), car theft and reselling (Morselli and Roy, 2008), outlaw motorcycle gang activity (Morselli, 2009a, 2009b; 2010); sex trafficking (Cockbain et al., 2011; Mancuso, 2014), street gang activity (Morselli, 2009b), prostitution rings (Morselli and Savoie-Gargiso, 2014), gun trafficking (Leuprecht and Aulthouse, 2014), and hacking (Décary-Hétu, 2014; Décary-Hétu and Dupont, 2012; Dupont, 2014). Researchers have extracted social network data from these sources about ties (e.g. communication and material exchanges, kinship, personal relationships, co-participation in crime events) and actor attribute data (e.g. operational roles, hierarchical positions, trust demographic characteristics) (see Appendix A). From such data, scholars have employed a variety of analytical techniques, including measures of centralisation, centrality, cohesion, clustering, flow-betweenness, the positional importance of actors (Cockbain et al., 2011; Duijn and Klerks, 2014; Leuprecht and Aulthouse, 2014; Mainas, 2012; Morselli and Giguere, 2006; Morselli, 2010, 2009b; Morselli and Savoie-Gargiso, 2014; Natarajan, 2006), and fragmentation and brokerage to reveal broad network structures (Décary-Hétu, 2014; Natarajan, 2000). Researchers have also analysed variation in network structures across time (Dupont, 2014; Morselli and Petit, 2007; Morselli, 2009b), variation in network types (Framis, 2014; Framis and Regadera, 2017), network resilience (Décary-Hétu and Dupont, 2012), positional importance relative to specific attributes, including sentencing outcomes (Morselli et al., 2013), operation roles (Framis, 2014; Mancuso, 2014; Morselli, 2009b), hierarchical positioning (Morselli, 2009a, b), as well as the simulated removal of actors and impact on crime scripts (Morselli and Roy, 2008; Morselli, 2009b).

Five studies used *law enforcement intelligence reports and threat assessments*, which are not typically available to the public, to examine various forms of criminal enterprise (Hashimi and Bouchard, 2017; Malm et al., 2010, 2011; Malm and Bichler, 2013). These studies have drawn on two reports/assessments (see Appendix B) sourced from Canadian federal agencies, including the Royal Canadian Mounted Police (RCMP) and the Canadian Security Intelligence Service (CSIS). From these reports, researchers have extracted social network data about ties (e.g. business affiliates, co-offenders, known friends and relatives), as well as actor attribute data (age, gender, criminal records, affiliations with criminal groups) (see Appendix B). Using this data, scholars have employed various analytical techniques, including calculating centrality, cohesion, homophily, constraint and efficiency and conducting Exponential Random Graph Models (ERGMs) to reveal different patterns of co-offending (Malm et al., 2011), structural variation according to tie types (Malm et al., 2010) structural vulnerability to disruption (Malm and Bichler, 2011), and determine the positional importance of actors (Hashimi and Bouchard, 2017; Malm and Bichler, 2013).

A variety of *offender databases* sourced from police and correctional services have also been used to provide information about crime events, offenders and arrests. These databases, sourced from the United States, Canada, the United Kingdom, Sweden and Belgium, take a number of forms, but typically include information on all reported crimes or all arrests made within specific geographic areas (e.g. a metropolitan area, an entire state). A total of thirteen studies relied upon such data to better understand gang membership (Grund, Densley 2015; McCuish et al., 2014; Papachristos et al., 2015; Rostami and Mondani, 2015), terrorist groups (e.g. Helfstein and Wright, 2011), illicit drug production (Malm et al., 2008), and co-offending (e.g. Bouchard and Konarski, 2014; De Moor et al., 2018; Englefield and Ariel, 2017; Iwanski and Frank, 2014; Morselli et al., 2015; van Mastrigt and Carrington, 2014). From these databases, researchers have extracted social network data about ties (e.g., co-participation in crime events, alleged co-participation in crime events, co-arrests, personal or professional relationships) and actor attribute data (e.g. roles, education, employment, crime types, status,

Table 1
Number of articles by data type.

Data Type	No. of articles	Appendix
Investigative reports	20	1
Law enforcement, intelligence reports, threat assessments	5	2
Offender databases	13	3
Prosecution files	7	4
Court files	17	5
Departmental inquiries or commission	2	6
Multiple sources	8	7

drug type, geographic region, race, age, citizenship, criminal history and mobility). Using these data, scholars utilized various analytical techniques, including calculating centrality, clustering, core-periphery analysis, homophily and Jaccard similarity indices, determining the spatial temporal distribution of actors and conducting regression and ERGMs (see Appendix C). Such analysis made it possible to illustrate structural variation across different networks (Helfstein and Wright, 2011; Rostami and Mondani, 2015) and time (Iwanski and Frank, 2014; McCuish et al., 2014; Morselli et al., 2015), and positional importance relative to investigations (Bouchard and Konarski, 2014), status, role (McCuish et al., 2014; Englefield and Ariel, 2017), crime type (Englefield and Ariel, 2017; Iwanski and Frank, 2014), geographic location (Malm et al., 2008). Researchers also analyzed the associations between ties relative to race (Grund and Densley, 2015), gender and age (van Mastrigt and Carrington, 2014), structure relative to status (Papachristos et al., 2015) and group type (Rostami and Mondani, 2019), and spatiotemporal spread (De Moor et al., 2018).

Scholars have also used *prosecution files* that include information collected and maintained by prosecutorial services in specific jurisdictions, usually in preparation for prosecuting criminal charges at trial. A total of seven studies utilized such data to provide deeper understanding of human trafficking (Campana, 2016), people smuggling (Campana, 2018) and drug manufacture and trafficking (Bright and Delaney, 2013; Bright et al., 2015a, b; Bright et al., 2017, 2018a). The files used for these studies were sourced from prosecutorial offices in Italy and Australia, and contained documents including witness statements, interviews with suspects, and surveillance records. The research teams who authored these studies constructed datasets (one for human trafficking, one for people smuggling, and one for drug manufacture and trafficking), from which social network data was extracted about ties (e.g. transfer of goods and services, communications, and co-participation in crime events), as well as attributes (e.g. demographics, roles, and possession of illicit resources) (see Appendix D). Across these studies, the authors employed various analytical techniques, including measures of centrality, quadratic assignment procedure regression, and stochastic actor-oriented models. These techniques provided insights into tie formation (Campana, 2016, 2018; Bright et al., 2018a), changes to network structure and positional importance over time (Bright and Delaney, 2013), the simulated impact of law enforcement interventions (Bright et al., 2017), and the positional importance of actors relative to different networks (Bright et al., 2015a) and different attributes, including money, drugs, equipment, skills, premises, physical labor (Bright et al., 2015b).

Network data obtained from various *court files* were the most frequently used by researchers. Seventeen studies sourced network data from courts (including trial and appellate) to examine gang violence (Bichler et al., 2017; Randle and Bichler, 2017), drug trafficking (Athey and Bouchard, 2013; Bright et al., 2012, 2014; Hofmann and Gallupe, 2015; Hughes et al., 2017; Jones et al., 2018; Morselli et al., 2013), conspiracy to commit terrorist acts (Bright et al., 2018b; Harris-Hogan, 2013), human-trafficking (Denton, 2016), and various criminal activities associated with Italian mafia syndicates (Agreste et al., 2016; Calderoni, 2012, 2014a, 2014b, 2015). These studies have drawn on a variety of different court files, sourced from the United States, Australia, Italy and Canada, and include transcripts of court proceedings, judgements, judges' sentencing remarks, pretrial court orders, and other judicial files, including evidence (e.g. wiretap transcripts) (see Appendix E). From these files, researchers have extracted social network data about ties (e.g. material and non-material exchange relationships, co-participation in crime events) and other attribute data (e.g. operational roles, hierarchical positions, gender, race, age, prior arrests). Using this data, the authors of these studies employed various analytical techniques, including calculating centrality, cohesion, transitivity, clustering, Jaccard indices, triad census, brokerage and fragmentation (see Appendix E). Such analyses were used to illustrate community sub-structures (Athey and Bouchard, 2013), the positional importance of actors relative to specific attributes, including, offender roles (Bright, 2015; Bright et al., 2012, 2018b; Calderoni, 2012, 2014a, 2014b, 2015; Hughes et al., 2017); offender-victim relationships (Bichler et al., 2017; Randle and Bichler, 2017), demographic characteristics (Denton, 2016; Jones et al., 2018), and the resilience of criminal networks to law enforcement intervention (Calderoni, 2012; Hofmann and Gallupe, 2015; Agreste et al., 2016; Bright et al., 2014).

Two of the studies canvassed in this review (Lauchs et al., 2011, 2012) have extracted data from reports of *departmental inquiries or commissions.* Both studies draw from an Australian commission of inquiry into police corruption (see Fitzgerald, 1989) to examine police corruption networks. From these reports, Lauchs and colleagues were able to extract data about ties (e.g. material and nonmaterial exchange relationships relating to giving, receiving and supporting bribery). These studies employ analytical techniques including calculating cohesion and centrality (see Appendix F) to reveal areas of resilience and vulnerability within the corruption network.

Finally, it is important to flag that researchers have also used *multiple criminal justice records* within a single study. Eight studies reported the use of more than one source of data from the criminal justice system to better understand police corruption (Costa, 2017), Medicare fraud (Meyers, 2017), outlaw motorcycle gangs (Rostami and Mondani, 2019), drug trafficking (Duijn et al., 2014; Berlusconi, 2013), conspiracy to commit terrorism (Harris-Hogan, 2013) and terrorist financing (Belli et al., 2015), motor vehicle theft and rebirthing (Berlusconi, 2013) and historical crime networks (Papachristos and Smith, 2013; Smith and Papachristos, 2016). These studies utilize combinations of different databases, investigative records, departmental commissions and inquiries, and court files from Australia, Italy, Canada, the United States, and the Netherlands (see Appendix G). Researchers were, from these multiple sources, able to extract network data about ties (e.g. social and business connections, telephone conversations and co-participation in crime events or crime records) and other attributes (e.g. demographics, status, operational roles, criminal charges and case outcomes) (see Appendix G). This data was analyzed using various analytical techniques that calculated cohesion, centralization, centrality, core-periphery analysis, cliques, brokerage and fragmentation, as well as conducted ERGMs These analyses were used to determine network structure (Harris-Hogan 2012), the intersectionality between distinct networks (Belli et al., 2015), multiplexity in networks (Papachristos and Smith, 2013; Smith and Papachristos, 2016), the vulnerability and resilience of networks to attempts at disruption (Duijn et al., 2014), as well as the positional importance of actors relative to data sources (Berlusconi, 2013), actor roles (Costa, 2017), actor demographics and case outcomes (e.g. criminal convictions, Meyers, 2017).

Taking an archaeological approach to working with criminal justice records

Whilst the use of such data offers unique insights into the study of offending, we acknowledge, as Becker did more than 50 years ago, that criminal justice records are incomplete and beset with challenges. Notably, such data includes only a sample of criminal events and offenders. Researchers who seek to analyze criminal justice records within a network paradigm must adapt their methods, analysis and interpretation to the specific challenges presented by the data. Much like archeologists who deal with incomplete data, criminal network researchers must 'dig' to *access* relevant data, *prepare* the artefacts for analysis in the knowledge that such artefacts are but a sample, and *engage in analysis and interpretation* of such artefacts giving due *consideration to the limits inherent* in the artefacts under study. As Morselli (2009b) noted, criminal networks are not simply social networks in a criminal context. The context is critical. Similarly, we argue that data challenges for the collection of social network data in a criminal context are not identical to those faced by researchers in non-criminal contexts. The illicit environment in which actors cooperate, including regulation and enforcement, influences the nature of the data, and therefore frames the ways in which it can and should be analyzed, interpreted, reported and understood.

The critical review of the literature undertaken for this current paper identified a number of distinct challenges encountered by researchers when working with such data. These issues were compiled by the authors using an inductive process to produce the following categorical list of data challenges, also reported in Appendixes A–G, including (1) negotiating data access, (2) ethical considerations, (3) ascribing network boundaries, (4) defining network ties, (5) coping with missing data, (6) validity of data, and (7) acknowledging the limits of generalizability. The distribution of the challenges across the articles reviewed is reported in Table 2. Further elaboration of these studies that report said challenges, in addition to our own critical observations about the surveyed literature as a whole is provided in the commentary below.

Negotiating access to usable data

The sensitivities surrounding the content of criminal justice records limit their availability to researchers (Rostami and Mondani, 2015). Such sensitivities are more applicable to some data sources not routinely made publicly available such as intelligence reports. While only explicitly mentioned in this single article reviewed for the purpose of this current paper, we suggest that gaining access to criminal justice records arguably remains one of the greatest challenges facing researchers. There was a time (circa 2000) that a researcher had to essentially beg for access to such data. Morselli (2009b) captures the fraught nature of data access by describing researchers' plight in "scrambling to obtain data" (p. 23). Access to criminal justice records was often times more serendipitous than designed (see Morselli, 2009b), the result of limited data availability and simply being in the right place at the right time, rather than the result of careful strategy and case selection. These challenges are clearly evident across the canvassed literature and beyond the single article that explicitly acknowledged this data challenge. Rather, we found that researchers frequently reused primary data sources, often using the exact *same data* across several studies (e.g. Bright et al., 2015a, 2015b, 2017). Such data was often originally sourced from only a handful of jurisdictions or institutions. For example, the five studies that utilize intelligence reports extract data from only two separate reports in a single jurisdiction (Canada), whereas those seven studies using prosecution files involve only three distinct data sources, obtained from two jurisdictions (Australia and Italy). More broadly, the included studies sourced their data from an extremely limited number of geographic regions, including Canada (33 %), Europe (29 %), Australia (19 %), the United States (16 %) and Asia (see Appendixes A–G). Given the difficulties accessing data, this is hardly surprising - researchers (like us) naturally want to leverage as much as possible from a single dataset. We suggest, however, that researchers need to acknowledge and confront these limitations, as the data that is easiest to locate or access may not be the data that will provide the most meaningful insights into the structure and operation of a given criminal network. That is, researchers may fall into the trap of asking "what can I do with this data" rather than seeking data which helps to answer key questions in their field. In our view, researchers must be willing and able to expand the scope of their inquiries to include new data that moves beyond the limited number of sources and jurisdictions currently considered across the literature.

Table 2
Number of articles by types of reported data challenges.

Data challenges	No. of articles
Negotiating access	1
Ethical consideration	5
Ascribing network boundaries	17
Defining network ties	6
Missing data	46
Validity	41
Generalizability	16
None mentioned	18

This is easier said than done. Gaining access to some types of criminal justice records is more feasible than are others. For example, judges' sentencing remarks can be accessed freely online by searching individual court websites or by searching online legal databases as AustLII in Australia, BAILII in the UK, and CanLII in Canada (e.g. Bright et al., 2012). Facilitating access to other sensitive criminal justice records such as police arrests data will almost certainly require negotiation (with access by no means being assured), and sometimes formal applications (including ethics applications) to the relevant gatekeepers. Data access procedures can be labor intensive, time consuming, and expensive. For example, offence records and police surveillance transcripts are usually held by police agencies, prosecution files are usually maintained by the relevant prosecutorial authorities in archival files, and court transcripts are usually only available by application to the relevant court. Access to some data, for example, court transcripts, may require payment of a monetary fee (e.g. per page) which can render such data expensive for researchers. Other data may be sensitive and require de-identification or anonymization (e.g. for offender records) (Rostami and Mondani, 2015). The process of accessing data, including application and negotiation may require significant time and perseverance from researchers. Researchers must navigate this terrain tactfully and with cunning, sometimes convincing gatekeepers that there are no risks or negligible risks to the agency and that the researcher's motivations are benign. Such challenges to data access will be amplified where longitudinal (i.e. panel) data is sought (Bright and Delaney, 2013; Bright et al., 2018b)

Considering ethical pitfalls

Five articles directly flag the ethical pitfalls associated with using criminal justice records – each stressing concerns over the identification of subjects through reporting practices (Bright et al., 2012; Décary-Hétu, 2014; Décary-Hétu and Dupont, 2012; Mainas, 2012; McCuish et al., 2014). These five articles demonstrated the need for researchers to consider such ethical issues when extracting, coding, and publishing from research that includes criminal justice records. Specifically, researchers should consider whether the data should be maintained and reported in de-identified or anonymized form, especially if sourced from open source data. On one hand, it may be preferable to publish names of individuals to ensure transparency and facilitate both replication and comparison with other research on the same group. On the other hand, names are not necessarily germane to research which typically seeks to explore broader issues around network structure and operation. While there may be an argument that researchers are using sources that are otherwise publicly available and therefore should be permitted to report names of individuals involved, a counter argument is that SNA imposes structure on otherwise unstructured data rendering connections between individuals related to criminal activity; and that such structure may not be apparent in the raw source data. Some individuals may be named in the data but not involved in criminal activity (e.g. family members, friends). For example, several of the studies reviewed here analyzed ties based on "kinship" or "legitimate business associates" (see Appendixes A–G). Including such people in the network and/or naming them may implicate them in criminal activity even when they played no part in such activity. Similarly, some individuals may be connected to others in the network, and even implicated in criminal activity, but never charged or convicted. Researchers therefore need to be mindful of the implications of their work from the outset and ensure that data is prepared and coded such a way that overcomes any potential ethical hurdles including any harms to subjects, criminal justice stakeholders or researchers. Of the 75 studies reviewed, only four reported identifiable data for the networks as a whole. That is, these studies reported the names of actors in the networks whereas other studies de-identified actors using alphanumeric codes or similar. Two were on terrorist networks (Bright et al., 2018b; Harris-Hogan, 2013), one on a police corruption network (Lauchs et al., 2012), while the other was on the network of Al Capone (Papachristos and Smith, 2013). All three involved cases in which the context and details were highly publicized, with much or all of the information in the public domain, and as such most if not all actors could have been identified even if they had been anonymized. Nonetheless, we argue that clearer guidelines are required for researchers around the need to de-identify actors in published research.

Ascribing network boundaries suitable to the data

Researchers who extract data from criminal justice records must clearly define a boundary for their network, preferably prior to commencing data collection (although this is sometimes impossible). Network boundaries may be based on a particular social structure (e.g. formal group membership), activity (involved in a specific activity), temporality (involved only across a particular time period), or geography (e.g. arrested in a particular metropolitan area). The two primary approaches to boundary specification are the realist approach (i.e. whether actors consider themselves part of the network or not) and the nominalist approach (i.e. the researcher defines the boundary based on a theoretical or conceptual approach). In practice, often researchers make a pragmatic decision about boundary specification as determined by the boundary as set by the information incorporated within a particular source of data, for example the boundary of the network may be formed by the scope of the law enforcement investigation (see Campana and Varese, 2012). That is, the network boundary ends where the police or court file ends. This can, of course, mean that some individuals will be excluded from the analysis even though they were involved in the criminal activity of the network, but simply did not fall within the scope of the investigation.

Sparrow (1991) makes reference to “fuzzy boundaries”, noting that there is “no obvious criterion by which players can be excluded or included with any one network analysis” (p. 262). The problem is exacerbated because the boundaries of criminal networks, as determined by law enforcement agencies, do not necessarily coincide with those of the criminal groups, and researchers may determine boundaries based on theoretical or practical considerations (Berlusconi, 2013). This issue was clearly demonstrated in Burcher and Whelan’s (2015) analysis of the terrorist network involved in the 2005 London bombings, where they demonstrate that entirely different results can be gleaned from the study of a single cell as compared to a larger network.

When considering the boundaries of their network, researchers must be sensitive to and acknowledge the limitations inherent in their data source(s). Such limitations were flagged in 17 of the studies reviewed for this paper (see Appendixes A–G), and demonstrated that network boundaries tend to be set by factors outside of the researcher’s control and are therefore difficult to specify with any degree of certainty (Malm et al., 2010). Network boundaries may be put in place by the focus of an investigation, the prosecutorial strategy or the outcomes of a criminal justice process (e.g. only individuals convicted of a crime). For example, investigative records, intelligence reports and threat assessments may be confined to jurisdictional boundaries, and any funding and time constraints encountered by law enforcement agencies (Duijn et al., 2014). As such, data tends to be collected and constrained within specific jurisdictions (e.g. regions, countries), with links to individuals outside that jurisdiction (including transnational links) being missing (Malm and Bichler, 2011; Malm et al., 2010). Networks derived from prosecution files may also be limited to investigatory boundaries (and their inherent limitations) (e.g. Bright et al., 2015a, 2015b). Elsewhere, those using offender databases may also be limited by the comprehensiveness of available data. For example, where gang membership is an inclusion criterion for a particular database, such membership will usually be defined by police, not by the researchers. Such decisions may therefore over- or under-estimate the nature of network membership (Papachristos and Smith, 2013). Finally, network boundaries derived using court files alone will also be necessarily bound by the totality data that is available. That is, boundaries tend to be based on a decision to include/exclude particular individuals as part of the investigative process, or to potentially make a stronger case against a particular defendant (Calderoni, 2014b; Jones et al., 2018). As such, the final network portrayed may be but a fragment of a potentially much larger network (Athey and Bouchard, 2013). We therefore suggest that it is critical that these details are explicitly flagged and accounted for in the methodological account each and every study utilizing criminal justice records.

When the literature was considered together as a whole, it was clear that a number of studies failed to clearly articulate the parameters of the sourced data with specificity (see Appendixes A–G), and therefore depict objectively meaningful network boundaries. We suggest that this can bring into question renderings of any subsequent analysis and interpretation. For example, numerous studies simply report using “court cases” (e.g. Denton, 2016), “judicial documents” (e.g. Agreste et al., 2016), or “intelligence files” (e.g. Mainas, 2012) without providing any further detail on the precise nature of such documents and the data derived therefrom.

Defining network ties with precision

Once the network boundary has been determined, researchers must specify the criteria for the existence or non-existence of ties between each pair of actors in the network. Sometimes this appears straightforward, such as in the case of phone records in which a phone call between two individuals represents a tie. But should all phone calls be considered a tie, or only those in which illicit activity is discussed? If two individuals are arrested at the same time and location, can we infer that they are co-offenders? The threshold for being ‘linked’ must be considered and clearly set and articulated by the researchers (e.g. knowing someone, friendship, meeting the other, supply of a particular commodity). In the criminal context, not all ties may involve illicit activity; how should such ties be coded? It is therefore critical that researchers provide a clear statement on how ties between actors were determined. Limitations related to defining network ties were explicitly flagged in 6 of the studies reviewed for this paper (see Appendixes A–G). Nonetheless, the types of ties reported in the studies reviewed for this paper depended somewhat on the type of data available, as it limited the extent to which different types of ties could be specified. For example, some data included details of meetings, others included telephone records, while other data types included information about the exchange of resources such as money. Therefore, the types of ties used by researchers are driven by the availability of data and specifically, the type of relational data collected by agencies within the criminal justice system. This data limitation was flagged across six of the articles reviewed for the purpose of this paper. Morselli and Roy (2008) reported having to restrict their focus to relationships supported by telephone and physical surveillance records, while Malm et al.’s (2011) analysis was restricted to co-offending ties only. Others also noted that such data can omit important information about tie direction (Bright et al., 2015a) as well as tie strength (Jones et al., 2018; Bright et al., 2014, 2018a).

This challenge was also observed as being an issue beyond those studies that explicitly flagged them as an issue. Overall, across the literature, network ties were generally poorly articulated. For example, some papers described ties simply as nondescript “relationship between two individuals” (e.g. Bright and Delaney, 2013; Harris-Hogan, 2013) - a description which lacks the necessary specificity and renders any interpretation of analyses difficult. Elsewhere, ties were articulated with more precision, but this was done inconsistently. For example, we found that studies focusing on “co-offending” operationalized such relationships in very different ways, including co-arrests (e.g. Englefield and Ariel, 2017), co-participation in an actual crime event (e.g. Iwanski and Frank, 2014); co-accused of committing a crime (e.g. McCuish et al., 2014), amongst numerous others. This has implications for the interpretation of any results and mean that studies that purport to study co-offending do not do so with consistency.

Coping with missing data

Above and beyond anything else, coping with missing data was the single most pervasive challenge facing researchers, being explicitly flagged across 46 articles (see Appendixes A–G). This is unsurprising, given that law enforcement and other criminal justice agencies only ever have a 'partial view' of the network (Morselli, 2009b). This means that criminal justice records may suffer from missing data including missing actors and ties. The implications of this can be significant, as the fundamental structure of the network can change when actors and ties are missing (Hofmann and Gallupe, 2015), especially when such 'missingness' is systematic (e.g. where peripheral actors are more likely to be missing). According to Morselli (2009b), there are two types of missing data: (1) missing data beyond the final network; and (2) missing data within the final network. The extent of missing data beyond the final network depends on the stage of the criminal justice system at which data is collected, with an inverse relationship between scope and accuracy. At earlier stages of the criminal justice system, scope is wide, but accuracy is low. The trade-off reverses at the latter stages of the criminal justice system. In terms of missing data within the final network, this is a problem of missing nodes and ties and means that central participants in the criminal network may be those who were central to the investigation. In other words, actors appear central not because they were well connected but because law enforcement agencies have more information about them and their contacts. As a rule of thumb, as one moves from investigation phase to judgments, the number of peripheral actors decreases while highly connected actors remain (although such actors will have fewer ties; Berlusconi, 2013).

Our review of the literature demonstrates that missing data is not random, but is indeed systematic. Faust and Tita (2019) argue that this is generally a consequence of the assumptions, methods, and priorities of the original data custodians. For example, scholars relying upon data from police investigations, intelligence reports, threat assessments and prosecution files note that their observed networks may be inaccurate or incomplete because some actors remain unknown, unidentified or mislabeled as being unimportant (Malm et al., 2008, 2010; Malm et al., 2011; Leuprecht and Aulthouse, 2014; Framis and Regadera, 2017; Duijn and Klerks, 2014; Décary-Hétu and Dupont, 2012; Bright et al., 2017; Bright et al., 2018a, a; Bright et al., 2015b). According to Bouchard and Malm (2016), such network data is biased toward representing some actors more than others, as more information may be collected on actors deemed central to the investigation (e.g. whose phones were tapped), those arrested and prosecuted (Morselli, 2010; Mancuso, 2014; Framis and Regadera, 2017; Duijn and Klerks, 2014). Sparrow (1991) argued that such data is often determined more by "prior subjective judgments of investigations than by objective reality" (p. 262). Furthermore, prosecutorial files may only contain information pertinent to prosecuting the specific case before them (i.e. may not have complete information from law enforcement), or be presented so as to simply secure an expedient conviction at trial (Leuprecht and Aulthouse, 2014). Considered together, the resultant lack of completeness can manifest in several ways, notably as missing actors, missing ties, insufficient information on type of tie or tie direction (Bright et al., 2015a).

We suggest that the above-mentioned missing data limitations have flow-on effects for other potential data sources. Offender databases, for example, may be incomplete as a consequence of unreported offences, unidentified or unimportant offenders (Papachristos et al., 2015; Rostami and Mondani, 2015; Bouchard and Konarski, 2014; Malm et al., 2008; Iwanski and Frank, 2014; Englefield and Ariel, 2017; Belli et al., 2015). Furthermore, such data may lack significant details relating to the offenders and offence characteristics (Bouchard and Konarski, 2014; Iwanski and Frank, 2014). Studies drawing upon court files are also impacted. Criminal actors tend to prioritize secrecy and concealment, and this leads to missing actors (especially peripheral actors) and ties (Bright et al., 2018b; Jones et al., 2018; Hughes et al., 2017; Hofmann and Gallupe, 2015; Calderoni, 2014a, 2014b; Calderoni, 2015; Athey and Bouchard, 2013). That is, some actors may remain undetected because they employ strategies to deflect attention (Calderoni, 2014a, 2014b; Mancuso, 2014). Long lasting investigations may reduce the impact of missing data, as lengthier investigations are more likely to 'sweep up' more of the peripheral actors (Calderoni, 2014a, 2014b, 2015). A focus on wiretap data means other types of interactions between actors may not be available (e.g. face-to-face meetings), so some ties will be missing (Agreste et al., 2016).

Despite these limitations, we agree with the point made by Berlusconi (2013), who argues that: "despite the probability of missing information, arrest warrants and judgments seem to be reliable data sources to identify key players regardless of whether a large proportion of peripheral nodes is missing" (p. 78). Supporting this point about a specific data source is a body of evidence demonstrating that centrality measures remain robust under small amounts of random error (e.g. Borgatti and Everett, 2006). That is, Borgatti and Everett (2006) found that if data collection misses 5% of ties, correlation between true and observed centrality values will lie in .90 s. Centralized networks are therefore generally more resilient to missing data (Smith and Moody, 2013).

Identifying potential threats to validity

As Berlusconi (2013) points out, it is not the aim of criminal justice agencies to render a complete representation of a given network for research purposes. Rather, such agencies rely on methods that may necessarily result in incomplete information, for example, direct observations, archival searches, informants, or witness testimony. This can lead to a raft of validity problems when working with criminal justice records that can impact negatively on the results of SNA. As such, research needs to identify, and where possible reduce potential threats to validity from the outset, as there are no conventional statistical tests to assess validity in social network research (Campana and Varese, 2012).

More than half (41) of the studies reviewed in this article flag a number of threats to validity that have the potential to skew the representation of a given network (see Appendixes A–G). Those drawing data from intelligence reports, threat assessments and investigations may potentially be working with data that includes biases introduced via the specific focus of police investigators (Hashimi and Bouchard, 2017; Malm et al., 2010). Interactions between law enforcement and illicit networks can impact directly on the structure and dynamics of the network. Actors within criminal networks do not sit idly by while law enforcement investigate, arrest, and imprison co-offenders. For example, arrests, intelligence leaks, and surveillance can all impact on relationships within the network (e.g. by undermining trust). Arrest data may create false links between offenders if caught together committing the same crime, even though there is no extant relationship between them (Iwanski and Frank, 2014). Data may also be biased by the focus or goals of the investigation (Morselli, 2009b; Morselli & Roy, 2008). That is, investigators targeting particular criminal networks (e.g. gangs) may elect to focus their investigations on high-ranking individuals (perhaps as a means to disrupt a network), or low-ranking individuals because it may be more likely to result in convictions (Malm and Bichler, 2013). Similarly, in the cases where wiretap data is used, only select conversations may be included within the investigatory files, such that data includes a reduced and non-representative set of all conversations (i.e. a form of purposive sampling) (Mancuso, 2014; Berlusconi, 2013). Telephonic and physical surveillance will not include all contacts between participants, so some ties will remain unobserved (Morselli and Roy, 2008; Agreste et al., 2016). This may be because a heavy reliance on communication data that covers only a short period is unlikely to depict all existing relationships (Mainas, 2012; Natarajan, 2006).

There are also potential validity problems associated with the use of prosecutorial and court files for social network purposes. Bias is likely to be introduced into such data sources due to the extent of offences detected (van Mastrigt and Carrington, 2014; Englefield and Ariel, 2017) or the focus of investigation (Bright et al., 2018a, 2018b; Bright et al., 2013; Bright and Delaney, 2013; Bright et al., 2015a, 2015b; Bright et al., 2017; Hofmann and Gallupe, 2015; Denton, 2016; Agreste et al., 2016; Calderoni, 2012). Some individuals who are suspected or charged with offences may ultimately be deemed innocent and therefore inappropriately included in the analysis (Rostami and Mondani, 2015).

Data sourced from the criminal justice system can also contain errors that can have implications for SNA. Data errors can essentially be of two primary types: accidental errors (e.g. transcription errors, poorly kept records) and intentional misinformation (aliases, inaccurate details provided by suspects and witnesses (Bright et al., 2015b, b). For example, a researcher's efforts to identify individual actors can be undermined by similarity of names, ethnic naming conventions, use of aliases, and transcription errors (e.g. spelling inaccuracies) (Malm et al., 2010, 2011; Natarajan, 2006). As a consequence, individual actors may be counted multiple times (e.g. due to problems ascertaining identification of actors) which can artificially inflate the size of the network (Malm et al., 2010). This can result in the underestimation of centrality for certain actors as her/his contacts may be split between two or more identities. Furthermore, individuals may intentionally remove incriminating evidence (e.g. wipe hard drives) and therefore appear to be less important (Décary-Hétu and Dupont, 2012). Additionally, data collected at the investigatory stage has not been scrutinized (i.e. not tested in court; Malm and Bichler, 2013).

Network researchers looking to draw upon criminal justice records need to be cognizant of the threats to validity presented for each source. Overall, the focus of criminal justice interventions (e.g. investigations and prosecutions) can distort centrality and centralization scores such that high centrality is a proxy for the focus of an investigation rather than the connectedness of actors. In other words, centrality and centralization scores are particularly vulnerable to distortion as a result of these issues, which is particularly problematic given that of the studies we reviewed 79 % of studies used this measure as a primary component of analysis, and 37 % of those used it as the sole component of analysis. Lessons can, however, be learned from previous research about minimizing the impact of such threats to validity. For one, providing a clear specification of 'seeds' used to construct the network and those actors who are targeted can help to evaluate the impact of any bias on results (e.g. assess the centrality scores of such seeds compared to non-seeds; see Bright et al., 2015a). Elsewhere, scholars point out the perils of relying upon only a single source of data (which may ultimately be comprised of small sub-samples potential connections) (Campana and Varese, 2012). To counter such issues, we note that scholars are increasingly seeking to triangulate their data - that is, using alternate types of criminal justice records to confirm the validity of nodes and ties within a given network (Bright et al., 2015a; Duijn et al., 2014). Court files and sentencing remarks, for example, can be particularly helpful in this regard insofar as they can be used to confirm charges and convictions so that innocent actors are likely to be identified and excluded (Calderoni, 2014b).

Conceding the limits of generalizability

As with most forms of empirical social research, SNA using criminal justice records presents unique challenges to generalizability. Such challenges were flagged in 16 of the articles reviewed (see Appendixes A–G). Several of these articles mentioned generalizability limitations regarding the applicability of the results of specific case studies to other jurisdictions or group contexts (Dupont, 2014; Grund and Densley, 2015; Bright et al., 2015b; Bright et al., 2018a; Hughes et al., 2017; Hofmann and Gallupe, 2015; Agreste et al., 2016; Bichler et al., 2017). Importantly, and as mentioned previously, the datasets used across the studies we reviewed were derived from a limited number of sources from only a few jurisdictions. For example, the generalizability of results drawn from analyses of data sourced from intelligence files in Canada is likely to be somewhat limited in other contexts. Elsewhere, articles flagged the implications from missing data (Helfstein and Wright, 2011, and also discussed above). Beyond these, our review of the literature demonstrated that there are three primary generalizability concerns relating to social network research using such data: (1) the type of criminal activity in the case study, (2) the historical nature of some data; and (3) the focus on detected networks.

Given the challenge of data access and the nature of law enforcement investigations, it is likely that any one study will focus on only one type of criminal activity (e.g. cocaine trafficking), notwithstanding some research SNA research examining poly-drug trafficking and poly-criminality (e.g. Hughes et al., 2017). Given the specific challenges of particular markets and market niches (e.g. Malm and Bichler, 2013), findings for one type of activity (e.g. cocaine trafficking) may not hold for other types of activity (e.g. trafficking cannabis or motor vehicles). Similarly, results for organized criminal activity such as illicit drug trafficking may not apply to terrorist networks given the different methods and motivations (see Morselli et al., 2007). As such, we suggest that the extant literature is currently limited in its scope - of the studies reviewed, the great majority examined drug trafficking, with only a few some examining other criminal networks related to hacking, terrorism, and human trafficking amongst others. Importantly, other forms of organized criminal activity, such as wildlife trafficking, were not examined by any of the studies in our sample.

The temporal nature of criminal justice records are also important to consider. Criminal networks are multimodal and dynamic (i.e. evolve across time), but data collected from investigations, threat assessments, offender databases and court files tend to be static (i.e. cross-sectional) (Bright and Delaney, 2013; Hashimi and Bouchard, 2017; Framis and Regadera, 2017; Duijn and Klerks, 2014). Furthermore, given the lengthy lead time for cases to make their way through the criminal justice system, criminal justice records are likely to be based on historical cases that have made their way through the criminal justice system including trial and appellate courts (i.e. collected via court files). Data used on such historical networks (e.g. networks in operation up to 20 years ago) may be limited of generalizability to more contemporary networks (e.g. due to legislative and technological changes; Bright et al., 2012). This is potentially problematic given that organized crime groups and activities tend to be dynamic, constantly changing to adapt to law enforcement pressure and technological advances (Morselli et al., 2007; Bright and Delaney, 2013). For example, methamphetamine trafficking has transformed in Australia since the early 2000s due to new manufacturing and distribution methods, and in response to police interventions. Case studies based on data from the 1990s may not apply to networks that operate in 2020 and beyond (e.g. see Bright et al., 2012). New methods may call for different resources and roles for actors, modified crime scripts and different network structures.

Finally, it is often argued that networks based on criminal justice records, particularly those derived from court files, may be unrepresentative because they are based on unsuccessful criminal networks (Hughes et al., 2017; Hofmann and Gallupe, 2015; Agreste et al., 2016; Bichler et al., 2017). That is, such networks have been disrupted and, in many cases, completely dismantled by law enforcement activity. Perhaps such networks differ in systematic ways from networks which are never dismantled (a kind of unknown unknown). However, many criminal networks are successful for long periods (years or even decades), even though they are eventually disrupted and dismantled by law enforcement agencies (Hughes et al., 2017). Further, actors who are involved in criminal networks such as those that traffic illicit drugs accept the risks of being caught and imprisoned, and such risks are incorporated into profits and payments. In other words, network actors are cognizant that they are likely to spend some time in prison as a result of their activities (Bright and Ritter, 2010).

Charting a way forward for social network researchers

In this final section we draw together the key challenges flagged in the above discussion and offer a number of recommendations for network researchers seeking to leverage data from criminal justice records. Much like archaeologists, researchers must consider innovative ways to collect data, while at the same time being alert to unforeseen opportunities for data extraction. In our experience, one way to combat problems with data access is for researchers to develop long-term research collaborations with law enforcement and security agencies. Such collaborative relationships may yield access to alternative data sources such as active (or more contemporary) data. When planning a study of this type, and particularly when planning to collect data from criminal justice records, we urge researchers to be alert to ethical issues. For example, as mentioned previously there is a pressing need for ethical guidance and consistency on the anonymization of data sets sourced from official data sources (Dupont, 2014; Décary-Hétu and Dupont, 2012). In our view researchers should, wherever possible, assign non-attributable identifiers to actors at the coding stage (e.g. unique alpha-numeric codes), so as to protect the integrity of both investigations, investigators, and proceedings, as well as actor identities (particularly those who may be contained within network boundaries, as affiliates and not direct participants in criminality) insofar as is possible. Unless criminal networks are extremely high profile or well established in the public record (e.g. the 9/11 attack network), such data should be anonymized.

With such data collection problems, we argue that researchers - like archaeologists describing a recently uncovered artifact - should clearly describe their method. At the very least, sampling methods, the nature of ties, and network boundaries should be clearly articulated (Bichler et al., 2017; Bouchard and Malm, 2016). In particular, we argue that researchers should be clear about precisely how the relational ties between actors within a criminal network will be specified. Scholars have, for some time, demonstrated that relational ties can (and do) manifest as different types of connections within any given social network, which can vary in terms of their nature, scope, and content (e.g. Knoke and Kuklinski, 1982; Wasserman and Faust, 1994). Wasserman and Faust (1994) propose a useful typology of ties that network scholars can use to precisely define, and provide consistency in, identifying the diverse relational connections that they may seek to measure. They propose that ties can be characterized an catalogued as being one (or more) of the following: (1) the *physical interactions* of actors (or their presence in the same place at the same time); (2) *individual evaluations* of another actor, which may include friendship, liking, respect, etc.; (3) *transactions or the transfer of material resources* that may involve buying, selling, lending or borrowing; (4) the *transfer of non-material resources*, including communication amongst actors or other information exchange; (5) *movement*, which may be physical (e.g. the migration from one location to another) or social (e.g. moving between social roles, job, or status); (6) *formal roles* whereby ties denote authority relationships (i.e. one actor has power/authority over another actor); and finally (7) kinship ties that reflect familial relationships (through descent or marriage) (p. 37). By taking such an approach, we suggest that researchers can begin to consistently operationalize ties across studies, and therefore more effectively draw parallels across (and build upon) the literature.

Distinguishing the various relational types from one another is a useful exercise in that it aids the researcher in narrowing the focus of the inquiry to the specific facets of the criminal network they seek to examine and measure. Such specification should be based on the context of the criminal environment in question, as well as the individual study's aims and objectives. The challenge for researchers is to ensure aims and research questions are consistent with the available data, especially when such aims and questions are likely to be influenced by the type of relational data available and the specificity with which ties are defined and operationalized. In our experience of working with criminal justice records, ties can and should be specified with as much detail as possible. One of the authors recalls defining network ties as "relationships" in earlier work and publications (some of which are included in our review) but later detailing the nature of ties with much more specificity (as the field and literature continued to mature). In selecting and then articulating ties, researchers may seek to explore a single relational type which is unidimensional in nature, or it could capture data on more than one type of tie and offer a multidimensional (or multiplex) perspective of the network. Doing so can provide insights into the various dimensions of a network, for example different types of resource exchange across the network (e.g. money, drugs, information) and whether some actors are involved in exchange of more than one type of resource (e.g. Bright et al., 2015a).

Along these same lines, when ascribing network boundaries, researchers need to ensure that they provide clear details about the sources of data and the boundaries of the network that have been imposed by the nature of the data (see Campana, 2018; Duijn et al., 2014 for well-articulated examples). That is, when defining the boundaries of any criminal network, we advise that researchers should endeavor to compile a comprehensive account of *all* relational elements associated with the criminal event(s). For example, researchers should not, for example, simply use names appearing in arrest records, or the subjects directly mentioned in wiretaps, but to also include other related affiliates who may be involved in the criminal network over time. Ouellet and Bouchard (2018) demonstrate the important and central roles that such affiliates can play within a criminal network, and argue that criminal network researchers should not rely upon a single official source, but instead also draw upon multiple and complementary data sources that provide insight into the full set of network actors and their relations comprising criminal events. Data from a wide range of additional sources (discussed further, below) can be used to supplement and cross-reference pre-existing data (Ouellet and Bouchard, 2018).

From our review of the literature, and from our experience in the use of criminal justice records s, we conclude that use of more than one data source can not only help to define network boundaries with precision, but also serve to overcome some of the limitations associated with any single source of data. For example, compared with a single source of data, the use of combination of sources can, amongst other things already discussed, limit problems of data validity and missing data (e.g. Bright et al., 2015a; Duijn et al., 2014). The triangulation of multiple sources can identify errors in one source, clarify facts, and confirm timing of interactions (Carley, 2015). But how many sources are optimal? Two sources appear better than one, but the relative value of a third or fourth source is not well understood (Carley, 2015). Further research is needed to resolve this question.

There are also no hard and fast rules as to what additional data sources might prove 'best', although some may bear more fruit than others. For example, from our review and from our own experience, prosecution files and other court records are of particular utility as such files tend to include data from a range of criminal justice records (e.g. transcripts of telephone intercepts, physical surveillance reports, and court transcripts) providing a form of triangulation within a single source of data. In addition, criminal network researchers have utilized myriad other sources to supplement their data, including interviews (e.g. Oulett and Bouchard 2018), surveys (e.g. Morselli, 2002), media reports (e.g. Bright et al., 2018b), as well as other observational or ethnographic techniques (e.g. Gallupe, 2016; Kenney and Coulthart, 2015).

There are a set of analytical techniques that can be used to identify, measure and overcome missing data limitations. For example, analysis of 'missingness' (missing data) can be used to determine the potential impact of missing data to provide some estimate of the confidence researchers may have in the data as collected (Koskinen et al., 2013). Inferential analyses, goodness-of fit procedures, and comparison of networks using statistical models such as ERGMs are also recommended (see further, Faust and Tita, 2019; as well as Bright et al., 2018b for an example of such procedures).

With respect to generalizability, researchers should provide clear and detailed statements about the network including its size, temporal, geographic and spatial characteristics, and details on the nature of the illicit activities undertaken by actors within the network. This must include a very detailed description of the data source itself. As noted above, some articles in our review simply named the source as "court files" without any further details. Enhanced clarity and details on such aspects (e.g. a detailed list of the range of documents included in a source of data; e.g. see Framis, 2014; Framis and Regadera, 2017 for an example of this) can facilitate clear statements on generalizability of results for each discrete study and allow such results to be contrasted with the results of other research. To assist in this regard, Bichler et al. (2017) argue that researchers should report normalized values (i.e. standardized centrality measures), so as to render comparisons across studies more meaningful. These types of comparative analyses will inform questions about the generalizability of results.

We close by stressing that it is not our intention to scare researchers away from engaging with criminal justice records. On the contrary, our aim is to encourage researchers to engage with criminal justice records to shed new light on crime and criminal collaboration. In our view, the use of criminal justice records through SNA presents unique and exciting new ways to study crime problems and can illuminate methods for effective crime prevention and reduction. It is our hope that the discussion and recommendations presented offer a useful path forward and will enhance consistency of research practice in the field of criminal networks. We believe that network researchers, both seasoned and neophyte, can benefit from adopting a set of consistent approaches to successfully navigate this challenging, yet fruitful terrain.

Appendix A. Investigative records

Data source	Study	Ties and attributes	Analytical technique	Data challenges
Description: Files related to multiple investigations: Telephone intercepts, eyewitness statements, suspect statements, surveillance data **Agency**: Dutch Police **Jurisdiction**: Netherlands	Duijn and Klerks (2014)	**Ties**: Kinship; Criminal relationship; affective relationship **Attributes**: *None listed*	Centrality Centralization Cohesion Clustering	Ascribing boundaries Missing data Validity
Description: Files related to two police investigations: Victim and offender interviews, case summaries, text message and video footage from mobiles, charge lists, court visits **Agency**: *Not listed* **Jurisdiction**: United Kingdom	Cockbain et al. (2011)	**Ties**: Evidence of a personal or professional relationship **Attributes**: *None listed*	Centrality	None
	Décary-Hétu (2014)	**Ties**: Digital communication **Attributes**: *None listed*	Centrality Cohesion	Ethics
Description: IIRC chat logs seized by the **Agency**: Sûreté du Québec **Jurisdiction**: Canada	Décary-Hétu and Dupont (2012)	**Ties** Digital communication **Attributes**: *None listed*	Centrality Flow-betweenness Fragmentation	Ethics Missing data Validity
	Dupont (2014)	**Ties**: Digital communication Attributes: Trust	Centrality Flow-betweenness	Generalizability
Description: Files related to four investigations: Search warrants, Telephone intercepts, asset seizure, photographic reconnaissance, interrogation transcripts, surveillance **Agency**: Judicial Police Unit of the Spanish Guardia Civil **Jurisdiction**: Spain	Framis (2014)	**Ties**: Co-attendance at meetings; Telephone conversations **Attributes**: Roles	Centrality Centralization Cohesion	None
Description: Files related to investigation: Search warrants, Telephone intercepts, asset seizure, photographic reconnaissance, interrogation transcripts, surveillance **Agency**: Judicial Police Unit of the Spanish Guardia Civil **Jurisdiction**: Spain	Framis and Regadera (2017)	**Ties**: Co-attendance at meetings; Telephone conversations **Attributes**: Gender; age; nationality; roles	Centrality Centralization Cohesion	Missing data Validity
Description: Case files relating to six police investigations **Agency**: *Not listed* **Jurisdiction**: Canada	Leuprecht and Aulthouse (2014)	**Ties**: Meetings, personal relationships; exchange of goods **Attributes**: Roles	Centrality	Missing data Validity Generalizability
Description: Telephone records; Europol intelligence files **Agency**: Hellenic Police Phone and Europol **Jurisdiction**: Greece	Mainas (2012)	**Ties**: Telephone conversations; known contacts **Attributes**: *None listed*	Centrality Cohesion	Ethics Validity
Description: Arrest warrant **Agency**: Carabinieri **Jurisdiction**: Italy	Mancuso (2014)	**Ties**: Telephone conversations Attributes: Gender; nationality; roles	Cohesion Centrality	Missing data Validity
Description: Telephone intercepts (Project Caviar) **Agency**: Montreal Police, RCMP **Jurisdiction**: Canada	Morselli and Giguere (2006)	**Ties**: Telephone conversations Attributes: Roles	Centrality	None
	Morselli and Petit (2007)			None
	Morselli (2009b)	**Ties**: Telephone conversations **Attributes**: *None listed*	Centrality Centralization	Ascribing boundaries Missing data Validity
	Morselli et al. (2013)	**Ties**: Telephone conversations **Attributes**: Criminal conviction	Centrality	None
Description: Telephone intercepts (Operation Springtime) **Agency**: Montreal Police, Sûreté du Québec, RCMP **Jurisdiction**: Canada	Morselli (2009a)			None
	Morselli (2009b)	**Ties**: Telephone conversations **Attributes**: Rank	Centrality	Ascribing boundaries Missing data Validity

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(*continued*)

Data source	Study	Ties and attributes	Analytical technique	Data challenges
	Morselli (2010)	**Ties**: Telephone conversations **Attributes**: *None listed*	Centrality	None
Description: Telephone intercepts (Operation Ciel) **Agency**: Montreal Police, RCMP **Jurisdiction**: Canada	Morselli (2009b)	**Ties**: Communication exchanges **Attributes**: *None listed*	Centrality	Ascribing boundaries Missing data Validity
Description: Telephone intercepts, physical surveillance, co-offending records and **Agency**: Montreal Police **Jurisdiction**: Canada	Morselli (2009b)	**Ties**: Communication exchanges, co-attendance at meetings, and co-arrest **Attributes**: Roles	Centrality	Ascribing boundaries Missing data Validity
Description: Telephone intercepts **Agency**: Montreal Police **Jurisdiction**: Canada	Morselli and Savoie-Gargiso (2014)	**Ties**: Telephone conversations **Attributes**: *None listed*	Centrality Centralization Clustering	None
Description: Surveillance files and interrogation transcripts (Operations Siren and Togo) **Agency**: Montreal Police, Provincial Police, Canadian Border Security Agency, Insurance Bureau of Canada **Jurisdiction**: Canada	Morselli and Roy (2008)	**Ties**: Co-participation in a criminal event **Attributes**: Roles	Centrality Brokerage Fragmentation	Ascribing boundaries Defining ties Missing data Validity
	Morselli (2009b)			Ascribing boundaries Missing data Validity
Description: Telephone intercept transcripts **Agency**: *Not listed* **Jurisdiction**: United States	Natarajan (2000)	**Ties**: Telephone conversations **Attributes**: Roles; status	Cohesion	None
Description: Telephone intercept transcripts **Agency**: *Not listed* **Jurisdiction**: United States	Natarajan (2006)	**Ties**: Telephone conversations **Attributes**: Roles, rank	Centrality Cohesion Clustering	Validity

Appendix B. Law enforcement intelligence reports and threat assessments

Data source	Study	Ties and attributes	Analytical technique	Data challenges reported
Description: Provincial Threat Assessment **Agency**: CSIS **Jurisdiction**: Canada	Malm et al. (2010)	**Ties**: Known relatives; friends; co-offenders; business associates **Attributes**: Age; gender	Centrality Cohesion ERGM	Ascribing boundaries Missing data Validity Generalizability
	Malm and Bichler (2011)	**Ties**: Known relatives; friends; co-offenders; legitimate business associates **Attributes**: Roles	Centrality Clustering Fragmentation	Ascribing boundaries Missing data Generalizability
	Malm et al. (2011)	**Ties**: Joint arrests **Attributes**: Ethnicity, gang membership	Centrality Cohesion Homophily Constraint Efficiency	Defining ties Missing data Validity
	Malm and Bichler (2013)	**Ties**: Known relatives, friends, co-offenders, or legitimate business associates **Attributes**: Gender; age; group membership	Centrality	Ascribing boundaries Missing data Validity Generalizability
Description: Provincial Target Enforcement Priority List **Agency**: RCMP **Jurisdiction**: Canada	Hashimi and Bouchard (2017)	**Ties**: Two individuals recorded in the same interaction with police **Attributes**: Gender; criminal history; status	Centrality	Ascribing boundaries Validity

Appendix C. Offender databases

Data source	Study	Ties & Attributes	Analytical technique	Data challenges reported
Description: Police files **Agency**: RCMP **Jurisdiction**: Canada	Bouchard and Konarski (2014)	**Ties**: Co-charges or suspected co-offending **Attributes**: *None listed*	Centrality Core-periphery analysis	Missing data
Description: Belgian National Genetic Database; Belgian General Police Database crime data **Agency**: Belgian Police **Jurisdiction**: Belgium	De Moor et al. (2018)	**Ties**: Co-participation in a criminal event (burglary, violet theft, lethal violence, sexual offences) **Attributes**: *None listed*	Jaccard index Spatial-temporal distribution	None
Description: All police reports (except traffic accidents)	Englefield and Ariel (2017)	**Ties**: Co-arrests **Attributes**: Status; crime type	Centrality	Missing data Validity

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Data source	Study	Ties & Attributes	Analytical technique	Data challenges reported
Agency: Sacramento Police Department **Jurisdiction:** United States				
Description: John Jay and ARTIS Transnational Terrorism Database **Agency:** Investigating authorities **Jurisdiction:** Indonesia; Philippines; Spain	Helfstein and Wright (2011)	**Ties:** Evidence of a personal; professional relationship **Attributes:** Education; employment	Cohesion Clustering ERGM	Generalizability
Description: Drug crime data held at the Institute of Canadian Urban Research Studies **Agency:** RCMP (British Columbia) **Jurisdiction:** Canada	Iwanski and Frank (2014)	**Ties:** Co-participation in crime event (drugs) **Attributes:** Age; gender; region; crime type; drug type	Centrality Cohesion Clustering	Missing data Validity
Description: Arrest and conviction records **Agency:** London Metropolitan Police Service **Jurisdiction:** United Kingdom	Grund and Densley (2015)	**Ties:** Co-participation in crime event **Attributes:** Race	EGRM	Generalizability
Description: Drug unit case files **Agency:** Vancouver Police Department **Jurisdiction:** Canada	Malm et al. (2008)	**Ties:** Co-participation in criminal event; familial relationship; suspected criminal association derived from surveillance **Attributes:** Age; gender; ethnicity; citizenship; employment; mobility; criminal history; geolocation	Centrality Regression	Missing data Validity
Description: Corrections Network (CORNET) Database **Agency:** *Not listed* **Jurisdiction:** Canada	McCuish et al. (2014)	**Ties:** Co-accused (court order) of participating in criminal event **Attributes:** Criminal history; status; roles	Centrality Cohesion	Ethics; Missing data Validity Generalizability
Description: Police files relating to all crime events **Agency:** Sûreté du Québec **Jurisdiction:** Canada	Morselli et al. (2015)	**Ties:** Co-participation in crime event **Attributes:** offence type; age; gender	Centrality Core-periphery analysis	None
Description: Arrest database **Agency:** Newark Police **Jurisdiction:** United States	Papachristos et al. (2015)	**Ties:** Co-participation in crime event **Attributes:** Status, age, race, gender	Centrality Cohesion	Missing data Validity
Description: National Swedish Police Intelligence database **Agency:** Swedish Police **Jurisdiction:** Sweden	Rostami and Mondani (2015)	**Ties:** co-participation in crime event **Attributes:** *None listed*	Centrality Clustering	Negotiating access Missing data Validity
Description: Swedish criminal register of suspected offenders - misstankeregistret and the Swedish gang database **Agency:** Swedish Police **Jurisdiction:** Sweden	Rostami and Mondani (2019)	**Ties:** Co-registration in a case **Attributes:** Status; offence type	Cohesion	Missing data Validity Generalizability
Description: Official dataset of notifiable criminal events **Agency:** A large UK police force **Jurisdiction:** United Kingdom	van Mastrigt and Carrington (2014)	**Ties:** Co-participant in crime event **Attributes:** Gender; age	Homophily	Validity

Appendix D. Prosecution files

Data source	Study	Ties and Attributes	Analytical technique	Data challenges reported
Description: Prosecution files **Agency:** NSW Office of the Director of Public Prosecutions **Jurisdiction:** Australia	Bright and Delaney (2013)	**Ties:** Relationship between two individuals **Attributes:** Roles	Centrality Cohesion	Validity
	Bright et al. (2015a)	**Ties:** Co-attendance at meetings; telephone conversation; exchange information or resources **Attributes:** *None listed*	Centrality Cohesion	Defining ties Missing data Validity
	Bright et al. (2015b)	**Ties:** Relationship between two individuals **Attributes:** Resources	Centrality	Missing data Validity Generalizability
	Bright et al. (2017)	**Ties:** Co-attendance at meetings; telephone conversation; exchange information or resources **Attributes:** Resources	Centrality Fragmentation analysis	Missing data Validity
	Bright et al. (2018a)	**Ties:** meeting, telephone conversation, exchange information or resources **Attributes:** roles	Stochastic actor-oriented models	Defining ties Missing data Generalizability
Description: Prosecution files **Agency:** Italian Prosecutor's Office **Jurisdiction:** Italy	Campana (2016)	**Ties:** Co-participation in crime event **Attributes:** Gender; place of residence; nationality; age; roles; stage of crime script; kinship; violence	Quadratic assignment procedure regression	None
Description: Indictments **Agency:** Anti-mafia Prosecutor's office **Jurisdiction:** Italy	Campana (2018)	**Ties:** Co-participation in crime event **Attributes:** Gender; stage of journey; task; roles	Quadratic assignment procedure regression	None

Appendix E. Court files

Data source	Study	Ties and attributes	Analytical technique	Data challenges
Description: Court files **Agency**: Los Angeles County court **Jurisdiction**: United States	Bichler et al. (2017)	**Ties**: Offender commits violence act against victim **Attributes**: Status	Centrality Cohesion Jaccard index Triad census	Missing data Generalizability
	Randle and Bichler (2017)	**Ties**: Offender commits violence act against victim **Attributes**: Status	Centrality Transitivity	None
Description: Court case files **Agency**: *Not listed* **Jurisdiction**: United States	Denton (2016)	**Ties**: Co-participation in crime event **Attributes**: Gender	Centrality	Missing data Validity
Description: Documents and exhibits from cases **Agency**: United States District Court **Jurisdiction**: United States	Hofmann and Gallupe (2015)	**Ties**: Communication **Attributes**: Roles	Centrality Centralization Clustering	Ascribing boundaries Missing data Validity
Description: Written decisions **Agency**: United States District Court **Jurisdiction**: United States	Athey and Bouchard (2013)	**Ties**: Positive relation between two actors **Attributes**: Roles	Cohesion Clustering Brokerage	Ascribing boundaries Missing data Validity
Description: Court orders issued by preliminary investigation judge **Agency**: Court of Milan **Jurisdiction**: Italy	Calderoni (2012)	**Ties**: Individuals talked or met; telephone conversations; co-attendance at meetings **Attributes**: Tasks; status	Centrality Cohesion Centralization	Validity
	Calderoni (2014a)	**Ties**: Individuals talked or met; telephone conversations; co-attendance at meetings **Attributes**: Tasks; status; rank	Centrality	Missing data
	Calderoni (2014b)	**Ties**: Individuals talked or met; telephone conversations; co-attendance at meetings **Attributes**: Tasks; status; rank	Centrality	Missing data Validity
	Calderoni (2015)	**Ties**: Meetings **Attributes**: Roles	Centrality	Missing data
Description: Court documents **Agency**: *Not listed* **Jurisdiction**: Italy	Agreste et al. (2016)	**Ties**: Telephone conversations **Attributes**: Rank	Centrality Fragmentation	Missing data Validity Generalizability
Description: Judicial sentencing remarks **Agency**: NSW criminal courts **Jurisdiction**: Australia	Bright et al. (2012)	**Ties**: Exchange of information; orders; goods; money or drugs **Attributes**: Roles	Centrality Cohesion	Ethics Generalizability
	Bright et al. (2014)	**Ties**: Exchange of information; orders; goods, money or drugs **Attributes**: Roles	Centrality Fragmentation	Defining ties Missing data Validity
	Bright (2015)	**Ties**: Exchange of information, orders, goods, money or drugs Attributes: Roles	Centrality	None
	Bright et al. (2018b)	**Ties**: Co-participation in extremist or terrorist acts **Attributes**: *None listed*	Centrality	Missing data Validity
	Hughes et al. (2017)	**Ties**: Co-participation in crime event **Attributes**: Roles	Centrality Cohesion	Missing data Validity Generalizability
Description: Court transcripts **Agency**: Supreme Court of New South Wales; Supreme Court of Victoria **Jurisdiction**: Australia	Harris-Hogan (2013)	**Ties**: Family; friend and acquaintance; attending meeting; exchanging telephone or email correspondence; travelling together; co-participation in training exercises; co-purchasing equipment **Attributes**: *None listed*	Sociogram only	None
Description: Federal court records from Public Access to Court Electronic Records (PACER) **Agency**: United States Federal Courts **Jurisdiction**: United States	Jones et al. (2018)	**Ties**: Co-participation in crime event **Attributes**: Gender; age; prior arrests; residency; location of crime; rank; prior criminal convictions; roles	Centrality Faction analysis	Ascribing boundaries Defining ties Missing data

Appendix F. Departmental inquiries or commissions

Data source	Study	Ties and attributes	Analytical technique	Data challenges reported
Description: Fitzgerald Inquiry Final report **Agency**: Government of Queensland **Jurisdiction**: Australia	Lauchs et al. (2011)	**Ties**: Bribe, payment, corrupt support, multi-relational **Attributes**: *None listed*	Centrality Cohesion	Missing data Validity
	Lauchs et al. (2012)	**Ties**: Bribes, transference of bribes, corrupt support **Attributes**: *None listed*	Centrality Cohesion	Missing data

Appendix G. Multiple criminal justice sources

Data source	Study	Ties & Attributes	Analytical technique	Data challenges reported
Description: US extremist crime database **Agency**: Department of Homeland Security **Jurisdiction**: United States	Belli et al. (2015)	**Ties**: some sort of social connection (e.g. business partnerships, relatives, neighbors and acquaintances) functional to the conspiracy **Attributes**: Gender; status; roles	Centrality Cohesion Centralization	Ascribing boundaries Missing data
Description: Investigative records (Projects Caviar, Siren, Togo, Ciel); Court files (judicial documents from of Milan) **Agency**: Montreal Police; RCMP; Sûreté du Québec; Canadian Border Security Agency; Insurance Bureau of Canada; Anti-Mafia District Directorate **Jurisdiction**: Canada and Italy	Berlusconi (2013)	**Ties**: Telephone conversations **Attributes**: *None listed*	Centrality Cohesion	Missing data Validity
Description: Departmental inquiry or commissions; Investigative files **Agency**: Chicago Crime Commission; Federal Bureau of Investigation **Jurisdiction**: United States	Papachristos and Smith (2013)	**Ties**: Co-occurrence of names in a record **Attributes**: *None listed*	Cohesion	Ascribing boundaries
	Smith and Papachristos (2016)	**Ties**: Co-occurrence of names in a record **Attributes**: Ethnicity; occupation; gender	Cohesion ERGM	Missing data
Description: Court transcripts, listening device transcripts **Agency**: Supreme Court of Victoria; Vitoria Police **Jurisdiction**: Australia	Harris-Hogan (2013)	**Ties**: Relationship exists between two individuals **Attributes**: Status	Core-periphery analysis Cliques	None
Description: Investigative records; Arrest records **Agency**: Dutch Police **Jurisdiction**: Netherlands	Duijn et al. (2014)	**Ties**: All criminal relationships **Attributes**: Roles	Centrality Fragmentation	Ascribing boundaries Missing data Validity
Description: judicial documents from pre-trial detention orders; investigation reports **Agency**: Tribunal of Florence; Special Operations Group of the Carabinieri **Jurisdiction**: Italy	Costa (2017)	**Ties**: Telephone conversations, co-attendance at meetings, business relationships **Attributes**: Roles	Cohesion Centrality Brokerage	None
Description: Court documents and federal indictments; Investigative records **Agency**: United States Federal Courts; Federal Bureau of Investigation **Jurisdiction**: United States	Meyers (2017)	**Ties**: Co-participation in criminal charges **Attributes**: Geographic location, criminal charges, gender, age, family relationships, country of origin, case outcome	Centrality	Missing data

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