Article

Exploring Internal Child Sex Trafficking Networks Using Social Network Analysis[1]

Eleanor Cockbain*, Helen Brayley** and Gloria Laycock***

Abstract This article explores the potential of social network analysis as a tool in supporting the investigation of internal child sex trafficking in the UK. In doing so, it uses only data, software, and training already available to UK police. Data from two major operations are analysed using in-built centrality metrics, designed to measure a network's overarching structural properties and identify particularly powerful individuals. This work addresses victim networks alongside offender networks. The insights generated by SNA inform ideas for targeted interventions based on the principles of Situational Crime Prevention. These harm-reduction initiatives go beyond traditional enforcement to cover prevention, disruption, prosecution, etc. This article ends by discussing how SNA can be applied and further developed by frontline policing, strategic policing, prosecution, and policy and research.

Introduction

Recent decades have seen a shift from reactive enforcement-led policing towards more proactive and collaborative approaches (Waters, 2007), like intelligence-led policing (ILP) and problem-oriented policing (POP) (Maguire, 1998). When policing makes 'much greater and much more systematic use of information' (Tilley, 2009, p. 2), new tools and techniques are required to provide analytical support at local and national level (Chainey, 2008). Faced with dramatic budget cuts (Dodd, 2010), social network analysis (SNA) offers a valuable opportunity to maximize current resources, without need for additional software or training. This article forms part of a pair of articles exploring the application of crime science tools to internal child sex trafficking: its complement is an analysis of crime scripting (Brayley *et al.*, 2011).

SNA

According to SNA, 'individuals are embedded in thick webs of social relations and interactions' (Borgatti *et al.*, 2009) which influence their behaviour. Although the term 'social network' commonly evokes images of Facebook or MySpace, it can

*Security Science Doctoral Training Centre, UCL, London. E-mail: eleanor.cockbain.09@ucl.ac.uk
**Security Science Doctoral Training Centre, UCL, London. E-mail: helen.brayley.09@ucl.ac.uk
***Jill Dando Institute of Security and Crime Science, UCL, London. E-mail: g.laycock@ucl.ac.uk

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apply to virtually any human interactions. SNA has helped explain phenomena as diverse as obesity (Christakis, 2007), globalization (Grewal, 2008), HIV (Rothenberg, 1998), and feminism (Philips, 1991).

A network is a set of 'entities', usually individuals, organizations, or commodities, connected by 'links' (i2, 2010), which symbolize relationships and interactions. If rearranged structurally, however, networks with identical components can function differently (McAndrew, 2000). A particularly important concept, the focus of much counter-terrorism SNA (Sageman, 2004; McAllister, 2004; Pedehzur and Perliger, 2006), is 'centralization'. A network's overall composition lies on a continuum from loosely dispersed (decentralized) structures to tightly knit (centralized) concentrations of entities. The more centralized a network, the less resilient it is to losing entities: loose terrorist networks can sustain 70% casualties before collapsing, compared to just 30% for highly centralized army units (McAllister, 2004). Understanding a network's composition enables interventions to exploit specific structural weaknesses.

SNA can also reveal the relative importance of each entity by analysing power as conferred by links to other network members, rather than individual personality traits (Hanneman and Riddle, 2005). This can pinpoint key relationships within criminal structures as targets for disruption.

Power is quantified using 'centrality metrics': robust mathematical functions which calculate scores for each entity based on its position in the network. These metrics have two main uses. First, average scores, ranges,[2] and standard deviations[3] indicate how power is distributed across networks, e.g. when power is evenly shared between members, ranges and standard deviations are usually small. Second, centrality metrics allow well-connected or influential entities to be identified. By targeting these figures, the police stand the best chance of disrupting or even disintegrating the whole network.

Most modern SNA software supports the automated calculation of centrality metrics: once networks are built, analysts need only run the metrics and interpret the results. Nevertheless, SNA is not completely objective: results are influenced by decisions on the entities included, types of links used and metrics applied. These choices depend in turn on the data available, level of detail required, and overall aim of the analysis.

Unfortunately, newcomers to SNA may be confused by the lack of standardization in the literature, e.g. different terminology is used for the same concepts, and the tendency of material to be either highly theoretical or extremely technical (McAndrew, 2000). Neither broad conceptual discussions nor the intricacies of statistics and computer science are of much practical use in policing. Occasional good introductions to SNA exist (e.g. Scott, 2000), but these are quite generic and none focuses on law enforcement.

Police have enjoyed a long history of mapping connections between actors and commodities involved in crime (Borgatti *et al.*, 2009), particularly organized crime, in line with initiatives such as Organized Crime Group (OCG) mapping. Generally, networks are built with data from on-going investigations and focus on offenders. The hand-drawn network charts once found on the walls of operation rooms have given way to their computerized equivalent. All UK police forces now use i2 Analyst's Notebook, a dedicated SNA software package with in-built centrality metrics, used by private security firms and law enforcement across the world, including America's FBI (Wakefield, 2003). Analysts regularly present network charts in court to demonstrate offending groups' structures. As the British police have

[2] Range is the difference between minimum and maximum scores in a set: e.g. if the highest score is 70 and the lowest 10, the range is 60.

[3] Standard deviation measures the level of variation between entities' scores (see Rowntree, 2000).

already embraced i2's network visualization capacity, the next step is to fully exploit its analytical potential. This article will demonstrate how SNA can use existing police data, software, and capabilities to shed light on an under-researched crime type and inform novel intervention ideas.

Situational crime prevention

Beyond enforcement alone, SNA can inform targeted interventions across diverse areas including detection, investigation, disruption, prosecution, prevention, and education. Most suggestions given here draw on Situational Crime Prevention (SCP), a theory which has proved increasingly attractive to UK police (Clarke, 1997). It was long assumed that criminality was somehow ingrained, whereas SCP sees criminals as rational decision makers who weigh-up costs and benefits before offending (Cornish and Clarke, 1986). According to SCP, most crime is opportunistic, requiring three factors to coincide (Cohen and Felson, 1979):

- willing offender;
- suitable target or victim; and
- absent guardian(s).

SCP aims simply to create conditions unfavourable to crime by doing one of five things (Clarke, 1997; Clarke and Eck, 2003):

- increasing perceived effort;
- increasing perceived risks;
- reducing rewards;
- removing excuses; and
- reducing provocations.

As conditions change, so too does the prospective criminal's cost-benefit analysis. Effective SCP can deter crimes by shifting the balance against the criminal act, often through simple and intuitive interventions addressing specific situational conditions. The main argument against SCP is displacement: crime is not prevented but pushed elsewhere. Yet, there is little empirical support for displacement and where proven it has been at low levels only (Guerette and Bowers, 2009).

Internal child sex trafficking

Under Section 58 of the Sexual Offences Act 2003 (OPSI, 2003), it is illegal to arrange or facilitate the movement of someone within the UK with the intent to exploit them sexually. This offence, internal sex trafficking, carries a maximum custodial sentence of 14 years (SGC, 2007). What we call ICST is the subset involving UK children (aged under 18 years). We exclude internationally trafficked children who are subsequently trafficked internally since their exploitation has a different profile. Since awareness is low and ICST often overlaps with better-understood offences (rape, child pornography, false imprisonment, etc.), it is rarely reported or recorded as internal sex trafficking. Consequently, official statistics on prevalence are misleading (CRIN, 2001).

A recent study into internal and international child trafficking victims in the UK found that a fifth of all victims were British, the second largest nationality in the sample (CEOP, 2009). Since there is no evidence that British children are trafficked except for sex, these cases probably represent ICST. Fieldworkers describe a hidden but widespread problem with far-reaching implications. Alongside trauma to victims costs to society include strains on the health care, benefit and criminal justice systems and community tensions. When authorities are perceived as negligent, litigation is an additional risk: parents of ICST victims attempted to sue Lancashire police in 2007,[4] while a victim of the equivalent crime in Holland successfully claimed €74,000 from her school (Dutch National Rapporteur, 2009). The first major police investigation into ICST was launched in 2009 and several operations have followed.

[4] Interview with police, March 2010.

Contrary to stereotypes of sinister paedophile rings, most child sex offenders act alone (Wortley and Smallbone, 2006). Smallbone and Wortley (2000, 2001) found that only 4% were involved in an organized network and 92% had no contact with other offenders prior to arrest. The ICST operations considered here feature multiple victims and offenders, suggesting ICST is more networked than most child sex abuse and thus well-suited to SNA.

Data

Our study covers 25 offenders and 36 victims in total, drawn from two major police investigations: Operations X and Y. The data used were typical of police investigations:

- victim records of video interviews (ROVIs);
- offender ROVIs;
- MG5 case summaries[5];
- text messages and video footage from offenders' and victims' mobile telephones;
- formal charge list (Operation X); and
- court visits (Operation X).

Creating ICST networks

We created two networks per operation: one each for victims and offenders. By focusing on a single type of character, we could run centrality metrics comparing homogenous groups, i.e. offenders with offenders and victims with victims. To ensure this, we also excluded third-party actors, e.g. facilitators, and ICST-related commodities, e.g. properties or cars. As only charged offenders and testifying victims qualified for inclusion, our numbers are conservative. Interested in what could be achieved with existing police resources, we used their standard software, i2 Analyst's Notebook (version 8).

For clarity, our key terms are defined in Table 1 above. With no standard set of links, we created ours based on the broad social bonds in our data. These were: relative; colleague/classmate; neighbour; friend; associate; and acquaintance. These six links cover all known ties but are not mutually exclusive, so two entities could be relatives and friends, for example. To prevent centrality scores being skewed by multiple links, we allowed only one link between any connected pair. We manually prioritized the link we believed to be the strongest or first, e.g. being related predates friendship. It was not always obvious from the data if entities, particularly offenders, were friends or simply knew each other. To ensure consistency, we created classification rules for a spectrum from acquaintance, through associate to friend. Table 2 summarizes these and other rules. Ideally, links are colour-coded to facilitate pattern-recognition.

On each network we ran three common centrality metrics: degree; closeness; and betweenness, defined below (i2, 2010 unless otherwise stated). We calculated individual entities' scores from 0 (low) to 100 (high) and descriptive statistics (mean, range, etc.) for each network.

Degree

This is based on an entity's direct links to others. Degree is relative to the size of the network: an entity with five links in a network of seven scores more highly than one with five links in a network of 100. High scores indicate well-connectedness.

Closeness

This is based on the shortest paths ('geodesics') from an entity to all others. High scores indicate ability to access other actors independently and quickly transmit/receive information and other commodities.

Betweenness

This is based on how often an entity appears on geodesics between other pairs of entities. High scores indicate 'gatekeepers', who control flows

[5] Formal case summaries prepared by police for the Crown Prosecution Service (Moreno and Hughes, 2008).

Table 1: Components of a network

Term	Definition
Entity	Component unit of a network, e.g. individual, organization, or commodity.
Link	Connection of some sort between two entities, e.g. kinship, communication, or the flow of goods.
Path	A route from one entity to another, via intermediate entities if necessary.
Length	The number of links in a path.
Geodesic	The shortest available path between A and B.

Table 2: Rules and symbols for links

Category	Rules
Friend	Friend is a stronger link than both associate and acquaintance. Labelled friend if socializing is regular or friendship is admitted.
Associate	Associate is a stronger link than acquaintance but weaker than friend. Labelled associate if seen together multiple times.
Acquaintance	Acquaintance is a weaker link than both friend and associate. Labelled acquaintance if seen together once or twice.
Relative	All relatives are believed to be at least acquaintance, if not associates or friends.
Colleague or classmate	All colleagues/classmates are believed to be at least acquaintances, if not associates or friends.
Neighbour	All neighbours are believed to be at least acquaintances, if not associates or friends.

between different parts of the network (Perer and Shneiderman, 2006). As gatekeepers often link otherwise unconnected clusters (Rowley, 1997), their elimination can cause network disintegration.

We applied these three complementary metrics (Freeman, 1979) to ensure a picture as balanced and comprehensive as possible. Scores on a single metric can mislead (Scott, 2000). A powerful gang leader, for example, might be linked directly only to a few (albeit influential) individuals and therefore score lowly on degree. In simple structures, entities often have similar scores across different metrics ('co-variance'). When scores diverge, as is common in complex networks, this suggests an entity's position is advantageous in some respects, but not in others (Christakis and Fowler, 2007).

As a simple visual aid, we re-sized entities in proportion to number of links (degree), making well-connected entities immediately recognizable. As re-sizing is only relative to others in the same network, no cross-network comparisons should be considered. For anonymity, we replaced entities' names with randomly allocated letters: Operation X's offenders are A*–N* and victims a*–y* and Operation Y's offenders are A–K and victims a–k.

Considerations

Before presenting our networks, we should emphasize a few considerations:

- Results can open up new perspectives and indicate certain solutions may be effective, but they cannot give the definitive 'right answer'.
- SNA compresses voluminous information to produce concise diagrams and metric scores, but cannot replace the comprehensive understanding of an operation.
- In the process of data mining, analysts will invariably discover material which, although not directly relevant to building networks, may

help contextualize or strengthen SNA findings. Consequentially, the discussion below includes references to interview data which complements or supports our SNA-based findings. We found no instances where interview data contradicted the SNA's results.

- Links between entities are difficult to establish if offenders (or victims) refuse to comment or lie when questioned. Sometimes gaps can be filled from other sources, e.g. surveillance or recovered telephones.
- As no average centrality scores ('baselines') exist for ICST groups, or any comparable criminal groups, it can be hard to judge what is 'high' or 'low'. We assessed scores relative to all four networks to enable comparison.
- If someone is identified early in an investigation, his/her acquaintances may be more likely to be discovered, thereby disproportionately increasing his/her centrality scores. As degree is especially affected, complementary measures alleviate misleading results.
- Networks are rarely uncovered in their entirety. This is a limitation of all real-world research and no reason to discount SNA.
- Our networks are specific to Operations X and Y: although some commonalities discovered here may prove typical, future networks will no doubt have unique features too.

Findings and implications

We discuss below key findings, together with implications for policing and possible interventions. These suggestions have not been evaluated and are intended primarily to stimulate debate and demonstrate how SNA can generate intervention ideas. Although our networks feature male perpetrators and female victims, other gender configurations are possible.

Offender networks

Figures 1 and 2 show Operation X and Y's respective offender networks.

Only one operation had clear ringleaders

Evidence. Operation X's network is highly dependent on I* and L*: I* is directly connected to all co-offenders, L* to all bar one. They are also prolific abusers, together responsible for 69% of the operation's charges. Aware of this double-act, Operation Y's police believed that a demographically similar pair, E and C, were equivalent ringleaders and focused on them accordingly. SNA showed, however, that neither man had a top score on any metric. An analysis of degree scores, the clearest marker of well-connectedness, indicated that Operation Y's network was far more decentralized with a more even spread of power. Although both networks enjoyed similar mean scores (29.9 for Operation X, 32.1 for Operation Y), Operation X's result was skewed by I* and L*'s extremely well-connectedness. Operation X's range (75.0, compared to 47.1 for Operation Y) and standard deviation (21.8, compared to 14.4 for Operation Y) were both high, suggesting real discrepancy in power distribution between individual members.

Implications. When a network is centralized around ringleaders, they represent the 'glue' binding the network and therefore form obvious targets for removal. As they are well-connected, this news of their arrest should travel fast and deter others. Covert surveillance might support such highly targeted enforcement.

SNA can test assumptions, counter personal biases, review investigative direction, and suggest appropriate interventions. For Operation Y, it indicated the absence of ringleaders. Consequentially it would be cheaper and more effective to chip away at the whole network. Offenders could be subjected to pressure ('increasing perceived risk'), e.g. by issuing Harbourer's Warnings (Kent County Council,

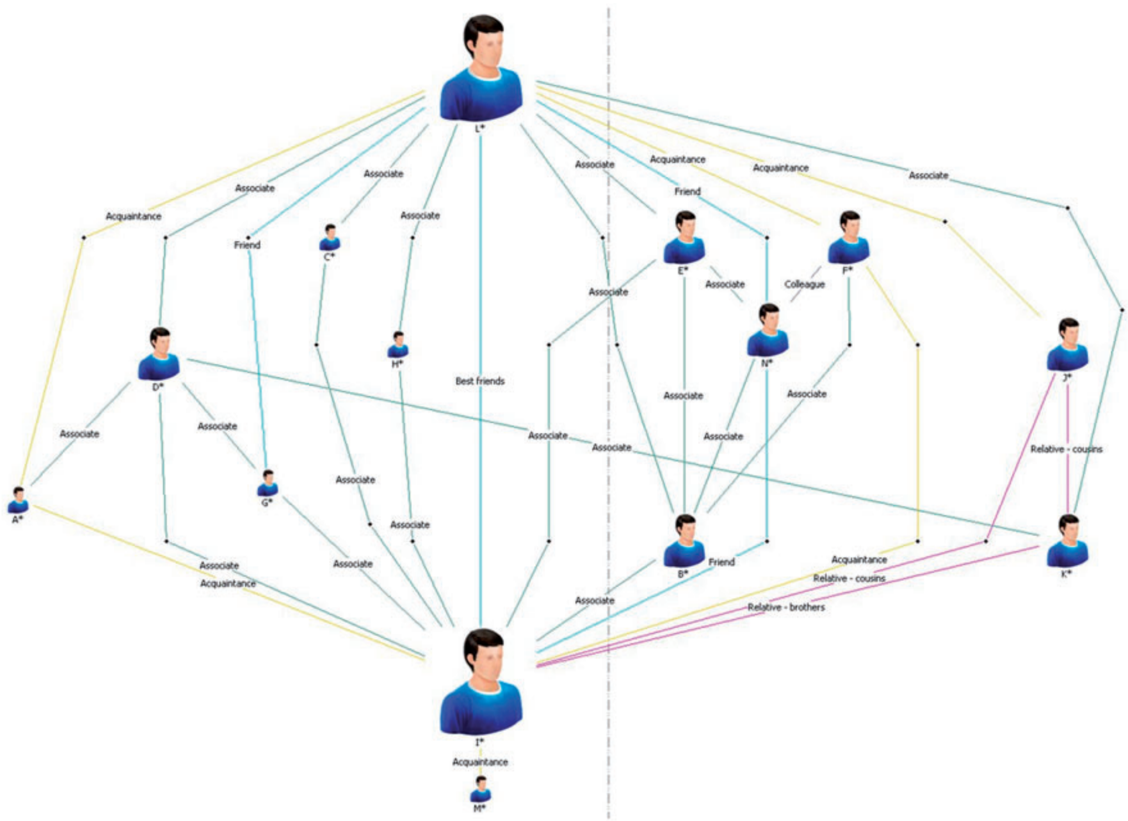

Figure 1: Operation X offender network.

2009). Those with important ICST-related commodities, like cars, might be targeted for driving offences to revoke their licenses and make cruising for victims harder ('increasing perceived effort').

Pre-existing social networks underpin offender networks

Evidence. Most offenders scored similarly on closeness, as emphasized by small ranges (6.9 for Operation X; 6.5 for Operation Y) and even smaller standard deviations (2.0 for both). As closeness indicates ready access to co-actors, relatively high averages (32.7 for Operation X; 29.8 for Operation Y) indicate tightly knit networks. Links include substantial social bonds, e.g. relatives, classmates, or neighbours. Interview data showed that much abuse occurred at parties or other social settings and men often abused *en masse.* All things considered, it appears likely that these offender networks formed from wider pre-existing social networks.

Implications. These networks which developed independently of and prior to ICST, contrast sharply with 'typical' abuse rings formed explicitly around shared interests in child sex abuse (Wortley and Smallbone, 2006). For network members at least, ICST is socially acceptable: awareness campaigns must emphasize its criminality ('Removing excuses'). As offences are not hidden from peers, there is a clear role for police informants. Emergent stereotypes characterize ICST offenders as Pakistani (BBC, 2004; Bindel, 2007; Reid, 2010; BNP, 2010), yet this ethnic clustering may primarily reflect

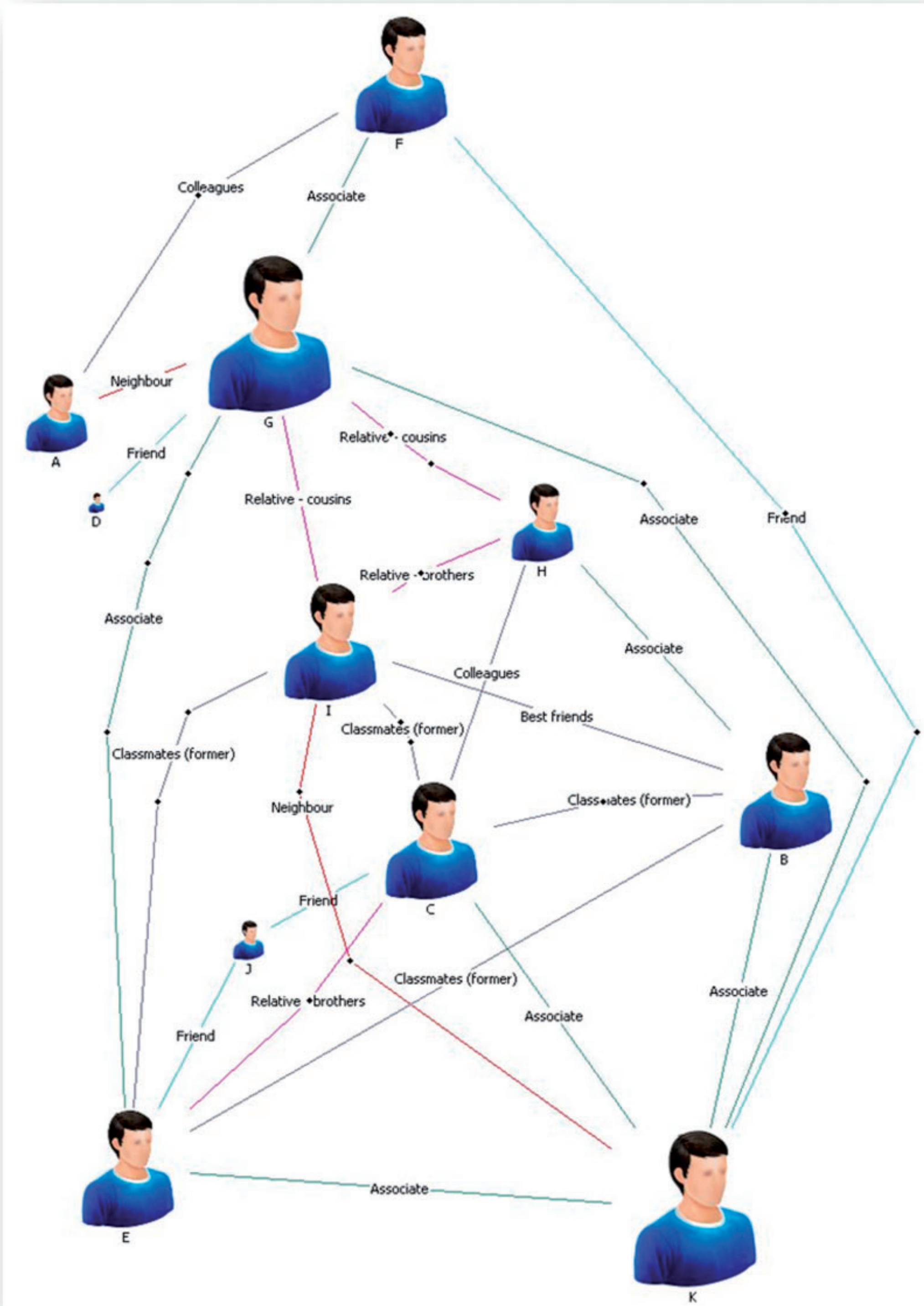

Figure 2: Operation Y offender network.

wider ethnic segregation, i.e. ethnically homogenous social networks.

The 'loverboy' stereotype is insufficient

Evidence. ICST offenders are typically characterized as 'loverboys': young men who groom victims by feigning romantic interest (CEOP, 2009; UKHTC, 2010). Some offenders fit the bill, e.g. Operation X's I* and L* Operation Y's E and C. Yet SNA found that G and K were the top scorers on all metrics and G was an obvious gatekeeper, scoring several times above average on betweenness. Both of these important figures were older and neither fit the loverboy profile.

Implications. Offender profiling should be treated carefully: fitting the profile is no guarantee of power.

Victim networks

Figures 3 and 4 show Operations X and Y's respective victim networks.

Victim targeting can be opportunistic

Evidence. In Operation X, four girls (16%) who were completely unconnected to the rest of the victim network and seemed therefore to have been picked up separately. Hidden constellations of victims might plausibly lie behind these lone victims, but victim ROVIs showed that many girls were approached randomly, indicating opportunistic targeting. Although Operation Y had no unconnected girls, they were identified through one another ('snowball sampling') and therefore inevitably linked.

Implications. If offenders target girls randomly, broad situational interventions are needed to raise

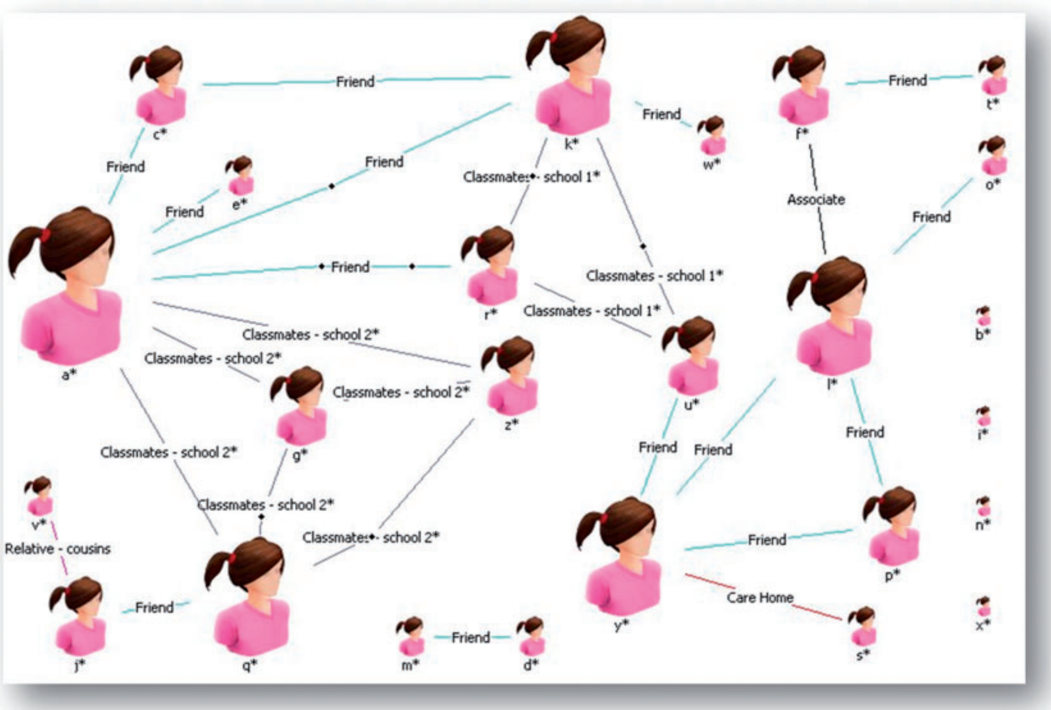

Figure 3: Operation X Victim network.

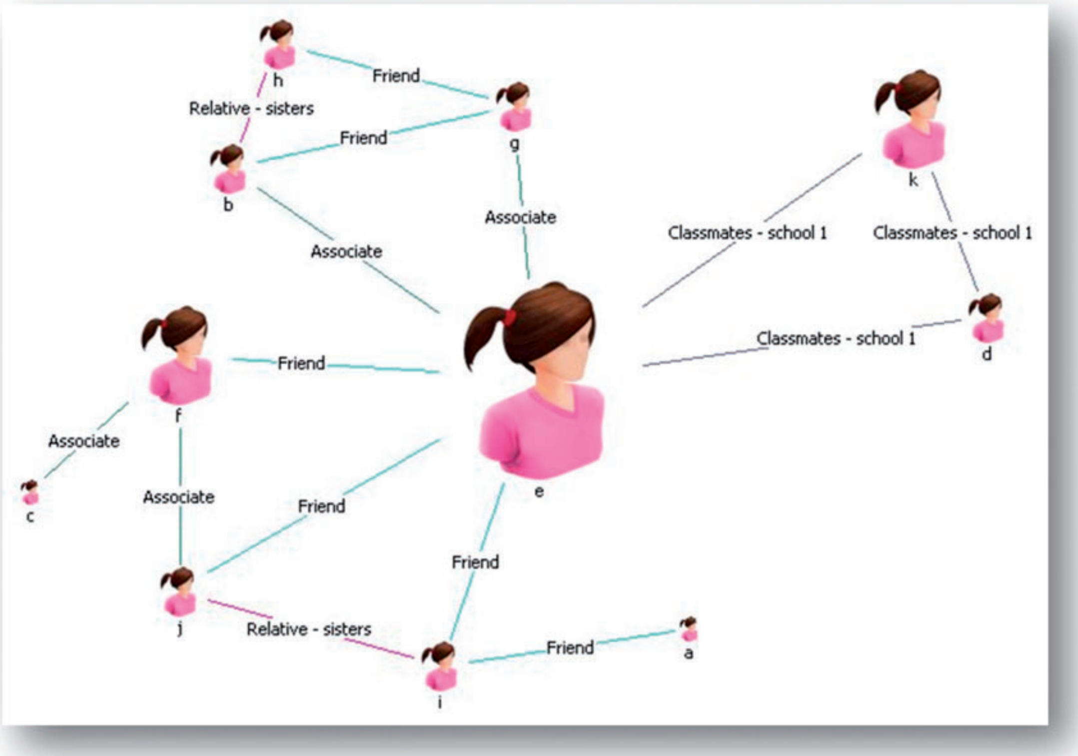

Figure 4: Operation Y Victim network.

awareness among all young girls ('increasing perceived effort'). Youth workers could explain that even if a girl enters an offender's car willingly, drinks alcohol, takes drugs, or accepts money, she is still a victim of crime. This might counter the sense of complicity fostered by offenders and encourage reporting ('increasing perceived risk').

Alternatively, situational interventions could target offenders, e.g. installing night-time sprinklers in parks where abuse occurs ('reducing perceived benefit'), or CCTV in pick-up locations ('increasing perceived risk').

'Girlfriend' figures aid recruitment

Evidence. Interview data showed that some girls are heavily groomed and believe they are in 'relationships' with offenders. These 'girlfriends' often recruit friends for abuse to please or pacify their 'boyfriends'. We identified three 'girlfriends' (a*, k*, and l*) in Operation X, forming nexus points around which other victims cluster. The most central 'girlfriend', however, was Operation Y's e, who was directly connected to 80% of victims. Her betweenness score of 62.1 was twice as high as any other actor in either operation. This indicated she was a gatekeeper linking otherwise unconnected parts of the network.

Implications. Identifying and targeting 'girlfriends', especially gatekeepers like e, helps dissipate networks and dries up an important recruitment channel ('increasing perceived effort'). As victims, these girls must be treated delicately, but if not dealt with properly they may become the next-generation ICST pimps or recruiters. This transition from victim to perpetrator features in international sex trafficking and presents challenges for prosecution (Monzini, 2000).

Not all victims are in care

Evidence. Many people believe ICST happens near exclusively to children in care.[6] Our networks show that only 8% of Operation X's victims were in care together and none of Operation Y's victims. In fact, friendship was the primary tie: 56% of Operation X's victims and 72% of Operation Y's had at least one friend in the victim network.

Implications. Our results challenge the myth that ICST offenders deliberately and exclusively target girls in care: broader interventions are necessary. Some girls were in care, however, usually entering the system post-abuse. Once there, however, their abuse continued, with offenders travelling between cities to re-abuse them. Initiatives with care homes might reduce repeat victimization ('increasing effort').

Not only was friendship the major link, but interview data showed victims were more vocal about their friends' abuse than their own. Initiatives which enable girls to report each other's abuse might prove fruitful ('increasing perceived risk').

Practical applications of SNA

We believe that the existing application of SNA could be usefully extended across the following four areas: frontline policing; strategic policing; prosecution; and policy and research.

Frontline policing

To be of tactical value, networks are best constructed in parallel with live operations, rather than once operations have concluded. They are dynamic: as new material emerges, they can be enriched and metrics re-run. Collaboration is key between officers who collect and process crucial data and analysts who build and analyse networks. NGOs and children's service providers could contribute supplementary material to enhance networks.

SNA could be further advanced by including the possession or flow of goods, e.g. money or drugs on networks, possible on existing software. For trafficking charges, an aggravating factor is the large-scale commercial exploitation of victims, demonstrable through clearly documented cash flows. Such inclusions might emphasize the organized crime aspects of ICST, thereby winning investigative funding.

Strategic policing

Senior officers might commission networks which go beyond offenders and victims to include critical third parties, about whom very little is currently known. Two examples are facilitators and clients. Facilitators enable ICST by turning a blind eye to suspicious circumstances, e.g. by allowing older men accompanied by (unrelated, often inebriated) young girls to buy alcohol or check in to hotels. Their behaviour gives perpetrators access to offence-related commodities and tacitly signals that ICST is permissible. Clients, in contrast, actively fuel ICST. Although not every individual offence was profit-led, many victims were pimped out at times. It remains unclear whether ICST clients actively prefer underage girls, or are driven by availability and price considerations. Our interview data showed, for example, that vaginal sex cost approximately £40: well below the market rate for non-trafficked adult prostitutes (Monzini, 2000). If these actors were included in SNA, it would be possible to explore new territory and identify alternative avenues for intervention.

At national level, officers could revolutionize the knowledge-base on criminal networks in general. Although we focused on ICST, SNA is useful for

[6] Based on our stakeholder interviews conducted February–August 2010.

any networked crime. A national police network database could be created as a repository for SNA data gathered by individual operations, subdivided by crime type. Relevant data might include charts, centrality scores, key findings, records of successful interventions, etc. Academics could be enlisted to establish baseline scores for centrality metrics and create a typology of networks. Once developed, such a resource could support new operations, by identifying from early data which type of network was present and potentially effective interventions. This database would necessarily be dynamic, so results should be re-evaluated at set intervals to ensure the material remained current.

Prosecution

ICST cases are difficult to prosecute, not least because of the huge volume of actors and victim credibility issues. If admissible under the laws of evidence, network charts and associated metrics might prove useful evidentiary aids. They could be presented to jurors to underline the organized nature of ICST or to emphasize the centrality of key perpetrators.

Policy and Research

As well as contributing to the national police network database discussed above, academics might explore ways of tailoring SNA to policing needs. One important example might be to explore ways of creating a single optimum composite metric to replace the three separate metrics discussed here, thereby saving valuable police time. While police focus on actual operation-specific networks, academics and policy-makers might explore reasons why networks develop, to inform early interventions aimed at preventing or disrupting networks' formation. Another critical area for attention is male-victim ICST and whether its network structures differ from the female-victim version of ICST analysed here. Local and national NGOs currently support male ICST victims and the sexual exploitation of boys is believed to be a vastly under-estimated problem (Barnardo's, 2011). Until more is known about male-victim ICST, it will remain unclear whether separate counter-strategies are required.

Conclusion

Police have long used networks in investigations to understand how suspects are interlinked. We have shown how networks need not be limited to offenders and that victim networks can prove useful too. Our study has demonstrated that more advanced SNA is possible at no extra cost. Existing data and software can be exploited in a more systematic and analytical manner to yield new insights. Results from SNA need not be addressed in isolation, but rather can complement and supplement findings from other sources, in a form of multi-method approach.

SNA is a valuable tool for supporting policing in several ways. First, it can guide investigative strategies and suggest targets for disruption or enforcement. Second, it can encourage an open-minded approach and counterbalance personal biases or assumptions based on prior experience, of individuals or of other operations. Third, it can identify areas of importance, such as 'girlfriends', which lie beyond the immediate police remit, highlighting areas for multi-agency collaboration. ICST is clearly a concern not just for the police and '[c]ross-cutting problems require cross-cutting solutions' (Stephenson, 2008). And finally, it can inform proactive interventions aimed at tackling ICST in a range of ways. ICST is a complicated and long-standing issue, well-suited to problem-oriented or intelligence-led approaches which recognize how preventive interventions can support 'smart enforcement' (Tilley, 2009). Nonetheless, it is crucial to remember that SNA is a useful framework for analysis, rather than a 'one-stop-shop' for answers. Ultimately, SNA can support experience and creative problem-solving, but it cannot be a substitute for them.

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