

**ASSESSING THE CORE MEMBERSHIP OF A YOUTH GANG USING TWO-MODE
SOCIAL NETWORK ANALYSIS**

Martin Bouchard
mbouchard@sfu.ca

Richard Konarski
konarski@sfu.ca

School of Criminology
Simon Fraser University
8888 University Drive
Burnaby, British Columbia, Canada
V5A 1S6

Preliminary draft submitted August 31, 2011

Prepared for the 3rd annual Illicit Networks Workshop
Montreal, October 2011

Acknowledgements. The authors would like to thank Teresa Pires of the Langley detachment of the Royal Canadian Mountain Police for help in retrieving co-offending data. Many thanks to Karine Descormiers who provided helpful comments on an earlier draft of this paper.

Abstract

The dynamic and sometimes diffuse nature of membership make gang boundaries sometimes difficult to discern for law enforcement officials or researchers, and even for members themselves. The current study draws on social network analysis of co-offending data to assess its utility in identifying the “core” membership of a youth gang active in a rural region of British Columbia, Canada. The ‘856 gang’ became a significant concern to the police and local population after criminal actions attributed to the group included two attempted murders, and the public attempted assassination at gunpoint of the father of one of the alleged 856 members. As the police were planning an intervention on the gang, a group of investigators set out to identify the “core” members of the gang through informal discussions and manual file reviews. This process led to the identification of 6 members who were arrested and charged in the summer 2007. For the purpose of this study, we used this set of 6 offenders and re-constructed their full co-offending network from incidents occurring between January 2003 and July 2007 as a two-mode social network. The findings reveal that a total of 60 offenders were potential members of the 856 gang, as defined by an arrest with one of the core 6 members identified by the police. Categorical and continuous core/periphery analyses of the co-offending data reveals that 13 out of 60 offenders could be defined as ‘core members’, including only 5 of the 6 offenders initially identified by the police, and that only three of the targeted members would have made a top 6 based on network centrality measures.

Introduction

The dynamic and sometimes diffuse nature of membership make gang boundaries sometimes difficult to discern for law enforcement officials or researchers, and even for members themselves. Yet, the temptation to classify gangs and their members into orderly, mutually exclusive groupings is high. Street observations of gang behavior, language, and symbolism generally fit an ideal type of a bounded and cohesive social group (Fleisher, 2005), especially at times of conflicts (Decker, 1996). Gang intervention programs are most efficient when it is able to differentiate between “core” and “fringe” members (Maxson, 2011), or between the minority of “organized”, and the majority of disorganized gangs (Spindler and Bouchard, 2011). Police interventions are designed to crackdown on a specific gang that should be easily discernable from the next.

An increasing amount of gang research, however, started to show that this idea of a bounded social group may in fact hide a much more complex set of interactions among a larger social (or criminal) scene that has consequences on gang behavior. Key to this shift is the use of social network analysis (SNA) in gang studies (Papachristos, 2006; Morselli, 2009). SNA allowed researchers 1) to realize that gang members were interacting with a larger social scene that included many non members, yet, criminally involved actors; 2) not take gang boundaries for granted, but to let them emerge from relational data.

At least two studies provided clear demonstrations of those two points. Combining the egocentric networks of two female members of the Vice Lords in Champaign, Illinois, Fleisher (2005) illustrated how such specific gang affiliation did not preclude friendship interactions with members of two other gangs:

North-end gang women identified themselves as members of Vice Lords, Gangster Disciples, and Black P-Stones, but gang affiliation had no necessary criminal or social obligations; there were no gang meetings, no script to memorize, no need to participate in gang fights or sell drugs, and no need to hang out with or feel personal closeness to fellow gang members. There were no fights supporting gang pride. Violence was personal and usually instigated by love relations gone awry. Most important, a gang affiliation did not impede social, economic, or personal relationships among north-end gang women (Fleisher, 2005: p. 126).

Fleisher’s (2005) study is important in demonstrating how different research designs may lead to different conclusions about gang boundaries: street observations seem to fit the cohesive,

territorial gang perspective while an analysis of social interactions suggested much more blurry boundaries between groupings. The fact that some gang studies rely on co-offending data, others on participant observation or conversations extracted from wiretap data should not be lost on researchers who interpret their results in light of prior studies.

This particular point is well illustrated in Morselli's (2009) reliance on wiretap data to examine the role of a major gang in a drug distribution trade network in Montreal. In launching three successive investigations targeting one gang (the Bo-Gars); the objective of the Montreal Police Department was clear: eliminate this gang which was thought to control drug distribution in the North part of Montreal. The Bo-Gars proved to be a rather elusive group. Of the 70 individuals identified as participants in the drug distribution trade over the course of these three investigations, only 23 were gang members, including 11 Bo-Gars members. Interestingly, gang members were not the most central players to this network: of the five individuals identified as the backbone of the distribution chain (highest betweenness centrality scores); only one was a gang member. The relatively minor role played by the Bo-Gars in the network may either be interpreted as an illustration of their peripheral role in the distribution trade uncovered by the investigations, or as a prime example of strategic positioning by key players (or leaders) who are able to remain at a secure distance¹ from the main distribution activities (Morselli leans towards the latter interpretation). This reminds us of the limitations of social network analysis, if used alone, in providing a clear picture of who the key players are in a network. Complementary information on the nature of interactions among network participants, as well as data on the functions and roles of network members is necessary for an accurate representation of individuals' significance in criminal and other networks.

The lessons learned from the above studies directly inform the problem at the core of the current case study. In early 2007 the city of Langley, British Columbia was facing a gang problem of its own. The '856 gang' became a significant concern to the police and local population after criminal actions attributed to the group included two attempted murders, and the very public attempted assassination at gunpoint of the father of one of the alleged 856 members. As the police were planning an intervention on the gang, a group of investigators set out to

¹ In the end, only 36% of the Bo-Gars were arrested, compared to 92% of other gang members, and 62% of the non gang members.

identify the “core” members of the gang through informal discussions and manual file reviews². This process led to the identification of six members who were arrested and charged in the summer 2007. When they settled on targeting six adolescents, the Langley Royal Canadian Mounted Police (RCMP) did not assume they had the “full” 856 gang. Instead, they figured they identified the “core” members, actors important enough to destroy what held the 856 gang together as a recognizable entity.

In this study, we assess the validity of the decision to target those six individuals as representing the core of the 856 gang³. We do so by providing a systematic analysis of the larger network of co-offenders who gravitated around the targeted members in the 4 years prior to police intervention. Given our two-mode research design, which relies solely on the co-offending associations of the six targeted 856 members, we are not in a position to offer a purely independent alternative method of identification that can be compared and contrasted. However, the additional, complementary information offered by a social network analysis of co-offending associations can help answer the two following questions:

- 1) Is the ‘core six’ 856 gang members as identified by investigators reproduced in the co-offending network? Is there a clear boundary between these six and other potential members once co-offending data is considered? More generally: Were the proper six members targeted?
- 2) Was ‘six’ an adequate number of members to target, or does a different number of offenders emerge as the core members in the co-offending network?

Data and Methods

Co-offending associations were retrieved in October 2010 by searching out all the police files related to the targeted six members of the 856 gang. The files for consideration mirrored the time frame utilized by the police investigators, spanning January 2003 to June 2007⁴. In

² Files were included for consideration if there was a reference to the 856 Gang. Beyond those criteria, there were no specifics in relation to the selection and identification process that was followed to identify the core six.

³ The six offenders targeted by the police in 2007 will be referred to as the “targeted six” to differentiate them with the “core” members identified through a social network analysis of co-offending data.

⁴ A change in the electronic records management system occurred on December 12, 2006 when the Langley RCMP switched from the Police Information Retrieval System (PIRS) to the Police Records Information Management Environment (PRIME). There was an unknown amount of attrition in the data from the PIRS. In that electronic system, files were automatically purged from the system once the retention period elapsed. For example, property crime offences may have a retention period ranging from two to five years. In reflecting on the range of files

addition to the inclusion of co-offending associations when two or more offenders were being officially charged together, it was deemed appropriate to include those categories where an offender was suspected of committing an offence, but for a variety of reasons insufficient evidence existed to proceed with charges. The broader focus provided more information on the co-offending associations of the targeted six 856 members, and is consistent with the research question which aims to assess the gang's core members. While the police intervention and the present study was concerned with youth offenders (under the age of 18), co-offenders were included for consideration regardless of age in order to obtain the most complete understanding of the co-offending network. Solo offending was, by definition, excluded from consideration in this study.

The data was coded directly as an affiliation network (Borgatti and Everett, 1997; Borgatti and Halgin, 2011; Faust, 1997); that is, offenders were included in the network to the extent that they were connected (i.e. affiliated) to at least one of the six targeted 856 members. In other words, co-offending ties between co-offenders were thus not coded if they did not involve one of the six members initially targeted. The data was thus treated and analyzed as a two-mode network with one mode representing the six targeted members and the other representing their co-offenders. This contrasts with the majority of network studies where the same set of entities is analyzed the rows and columns of a matrix. Note that each member of the targeted six members was allowed to co-offend with one or more of the other five⁵. In those instances, both targeted members were included as co-offenders in mode 1 (e.g. A_1 and B_1), with an affiliation link to one another through mode 2 (A_1 to B_2 ; B_1 to A_2). Following the logic of affiliation network data, one association between the targeted six members thus created two co-offending entries.

Multiple counts of co-offending with a member of the targeted six were coded to create a valued, two-mode co-offending network. More frequent co-offending associations with members of the targeted six were thus taken into account to determine the core of the 856 gang. Co-offending associations for a single individual ranged between 1 and 18, with a mean of 3.07 total associations with the targeted six members.

examined by the investigative team dating back to January 2003, it should be expected that a small number of these files were purged at the time of this study.

⁵ In theory, the targeted six are treated as equals to other potential 856 members in mode 1. In practice, each member of the targeted six did not have an equivalent chance of inclusion because they could not co-offend with a maximum of 5, as opposed to six offenders. Because self-associations were excluded, no member of the targeted six has the possibility of obtaining the maximum centrality scores. However, note that additional analyses allowing for the six self-associations did not substantively change the results of the study.

Centrality measures

In affiliation networks, individuals (mode 1) are connected to others only through an event (mode 2). We do not know whether two individuals actually know each other, but their common presence in one or more events increases the likelihood of social interaction among them (Borgatti and Halgin, 2011). In this study, offenders (mode 1) are connected to the extent that they have a common co-offending association to a member of the targeted six (mode 2)⁶.

The objective of this study implies that we calculate centrality scores adapted to the logic of two-mode networks. In such cases, an actor is central relative to the events (targeted six) it connects to. Conversely, events are central relative to the size or nature of their memberships (Faust, 1997). Two measures of centrality are used in this study, *degree*, and *eigenvector*. From the point of individuals, degree centrality refers to a binary, normalized measure of the number of ties offenders have with members of the targeted six. The number of maximum of possible ties is six (five for members of the targeted six in mode 1). For members of the targeted six in mode 2, degree centrality refers to the normalized number of ties they have with the full set of co-offenders in the network. Normalization is important to the extent that we wish to directly compare the degree centrality of both actors and events (Borgatti and Halgin, 2011).

In eigenvector centrality, the centrality of an entity's connections is also taken into account. This might be important for our purposes given our objective to find "core" members, as opposed to just any type of affiliation to the 856 gang. In two-mode networks, an actor scores higher in eigenvector centrality to the extent that it is connected to central events (Borgatti and Everett, 1997; Faust, 1997). In our case, an offender's eigenvector centrality score is proportional to the sum of centralities of the targeted six members he is connected to (and vice-versa for eigenvector centrality scores of the targeted six members). All network measures are calculated using UCINET 6.352 (Borgatti et al. 2002); mathematical details can be found in Borgatti and Everett (1997), as well as Faust (1997).

Co-affiliation

Affiliation data may also be transformed into a one-mode matrix where a tie exists between two individuals if both are connected to the same member of the targeted six. In such

⁶ As noted earlier, members of the targeted six were also considered as co-offenders for the purpose of answering the research question on whether they belonged to the core of the 856 gang.

cases, these actors are said to be co-affiliated, and the new person by person matrix may be analyzed using standard one-mode tools (Borgatti and Halgin, 2011). The more affiliations in common to members of the targeted six, the stronger the connection between two offenders. The co-affiliation matrix will be used to determine whether the network exhibits a core-periphery structure (Borgatti and Everett, 1999).

Results

The analysis of co-offending data reveals that 54 previously unidentified offenders were arrested with one of the targeted six members identified by investigators between 2003 and 2007. If we consider that members of the targeted six were also “allowed” to co-offend with the other five (that is, they were allowed to act as co-offender in mode 1 as well), we have a network of 60 offenders (mode 1) who co-offended with at least one member of the targeted six (mode 2). This represents the co-offending social environment in which the targeted six members were embedded between 2003 and 2007. A graph representation of the 856 co-offending network is presented in Figure 1 below⁷. The red squares represent the targeted six members, and the blue circles are the co-offenders. The targeted six as co-offenders in mode 1 were circled to ease identification⁸.

Figure 1 first shows that not all targeted six members have similar patterns of connections. CaP, for example, is the center of a star network involving as many as 18 actors with no connections to the rest of the targeted six. His unique patterns of contact has him standing on the left side of the graph, yet close to AD with which he shares a few connections (TyS, DS, CS, BL, AdS, TaS, JW, BoS, TyD). CaP is the most connected member of the targeted six, and his network position gives him the highest degree centrality score among his peers (see Table 1 below). Yet, CaP only ranks third in eigenvector centrality because the majority of his connections are not connected to any other members of the targeted six. The eigenvector scores of TyS and AD reveal that their connections are more central to the overall network.

⁷ Using NETDRAW 2.113 (Borgatti, 2002).

⁸ We used spring embedding with equal mode length bias for the graph layout.

Figure 1. Two-mode co-offending network of the targeted six 856 gang members, 2003-2007

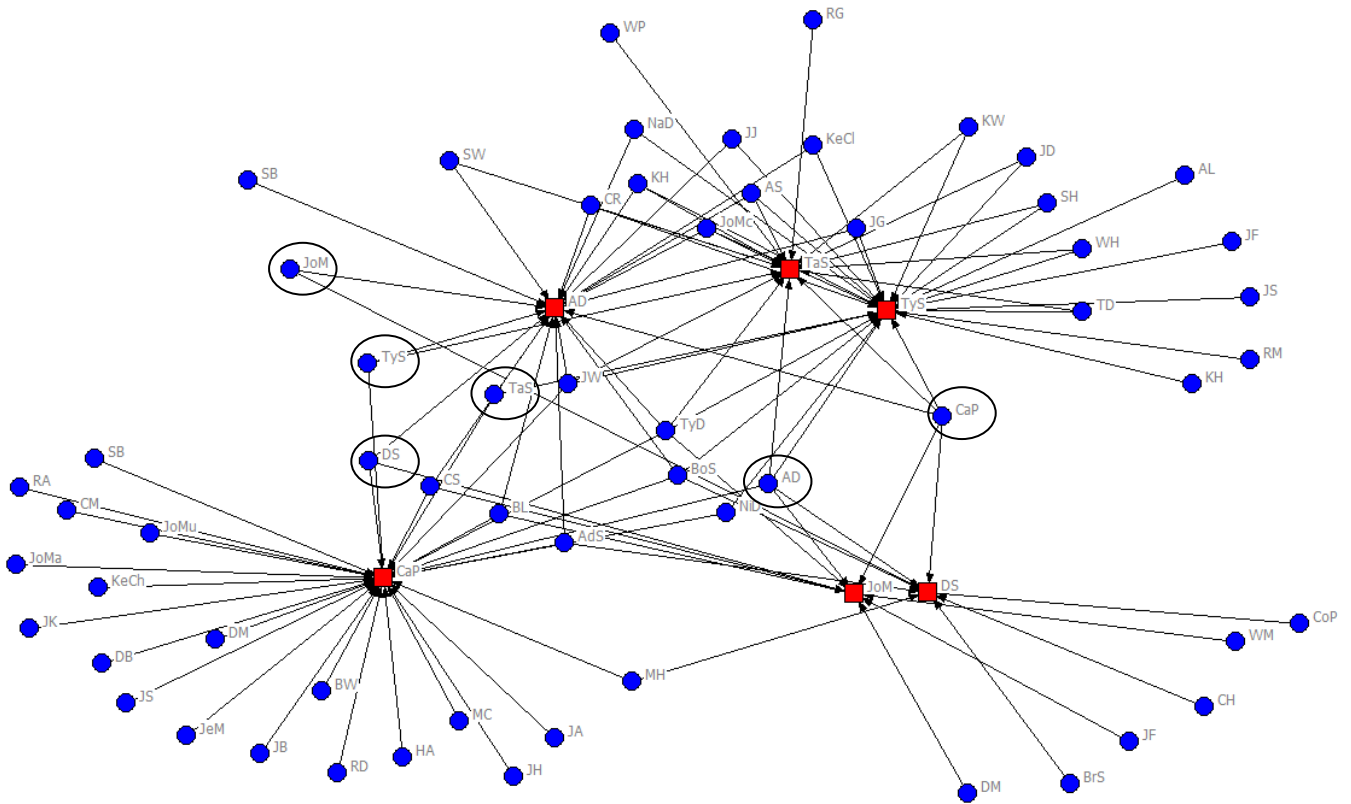


Table 1. Two-mode degree and eigenvector centrality scores of the targeted six 856 members

	Degree	Eigenvector
CaP	0.500	0.471
TyS	0.417	0.551
AD	0.350	0.510
TaS	0.283	0.398
DS	0.150	0.152
JoM	0.150	0.182

Not all members of the targeted six co-offended with the other five (Table 2). CaP and AD are the only ones to have done so, including five times together. DS, TaS, and TyS co-offended with three out of five, and JoM was only arrested with DS and AD over a period of almost five years (and only once with each). Either this is a sign of the targeted six not being as

cohesive as the investigators projected them to be, or this is an artifact of the research design relying on official data.

Table 2. Number of co-offending associations within the targeted six 856 members

	DS	JoM	TaS	TyS	CaP	AD
DS	-	1	0	0	4	3
JoM	1	-	0	0	0	1
TaS	0	0	-	5	1	3
TyS	0	0	5	-	3	6
CaP	4	1	1	3	-	5
AD	3	1	3	6	5	-

What was intriguing is that other co-offenders emerged as much more central to the targeted six. A total of 22 other offenders had at least two connections with the targeted six, and as many as 10 of those had connections with three different members of the targeted six. JW, for example, was arrested multiple times with each of TaS, TyS, CaP, and AD (12 total connections).

Should JW have been part of the targeted six, and should JoM be excluded? From a strict degree centrality perspective, and should we only have to choose six offenders to target, the answer would be yes. Table 3 presents the top 15 degree and eigenvector centrality rankings for the two-mode 856 co-offending network. As we can see, five offenders stand out in being highly connected with the targeted 856 members: CaP, AD, TyD, JW, and BoS. Only the first two are members of the targeted six, the other three are not. The last ten offenders completing the top 15 have an equal amount of connections to the targeted six, a list which includes DS, TyS, and TaS, but not JoM. Based on this information alone, the decision to target those five offenders is not unreasonable, with the exception of JoM. Should only six be chosen, a case could be made for TyD, and JW, and BoS be included in lieu of three of the original targets. Based on his eigenvector score (.210), TaS would complete the top six (and DS and TyS would not have made it). Given the small differences between centrality scores in the top 15, however, the real question is whether the “core” 856 gang should actually be reduced to only five or six offenders, an issue to which we turn below.

Table 3. Two-mode degree and eigenvector centrality for top 15 offenders

	Degree	Rank (degree)	Eigenvector	Rank (Eigen)
CaP	0.833	1	0.245	3
AD	0.833	1	0.240	4
TyD	0.833	1	0.289	1
BoS	0.667	4	0.230	5
JW	0.667	4	0.264	2
DS	0.500	6	0.159	12
TaS	0.500	6	0.210	6
TyS	0.500	6	0.189	11
AdS	0.500	6	0.155	15
BL	0.500	6	0.159	12
CS	0.500	6	0.159	12
JoMc	0.500	6	0.200	7
CR	0.500	6	0.200	7
KH	0.500	6	0.200	7
AS	0.500	6	0.200	7
JoM	0.333	16 ^a	0.091	27

Note. Targeted six in bold

a. Twelve others tied at rank 16.

Core/periphery analyses

Some SNA tools examine the data to find whether it exhibits a core/periphery structure. That is, whether a densely connected subset of actors can be observed and significantly differentiated from a more sparse peripheral set of actors (Borgatti and Everett, 1999). Those methods are intuitively appealing for our purposes, which consists in finding whether a closer analysis of the co-offending network matches what the investigators identified as the core of the 856 gang.

In UCINET 6.352, core-periphery analyses are available for data structured as two-mode networks, and also for the same data after transformation into a one-mode, co-affiliation network. Both types of analyses provide complementary information. The two-mode analysis will aim to identify a core of co-offenders that is more densely connected to a core of the initial six gang members. In addition to preserving the logic of data collection, the two-mode analysis has the advantage of identifying important players in both modes, including among those who were initially targeted (i.e. “a core among the core”). Conversely, this particularity also acts as a disadvantage. The algorithm forces a separation among the initial six members that may or may

not be fruitful. The one-mode analysis has the advantage of not forcing this separation, treating connections to any of the initial six members equally. An added advantage is that the one-mode analysis handles a categorical as well as continuous core/periphery analyses. In other words, instead of treating actors as either members of the core or the periphery, the continuous analysis calculates a “coreness” score, then aims to find a breaking point in the score distribution to suggest a “core” and a “periphery” (Borgatti and Everett, 1999).

Table 4 presents the results of categorical two-mode and one-mode core/periphery analyses, as well as a one-mode continuous analysis. Starting with the two-mode analysis, a core of 12 members is suggested, identified through their affiliation to three core actors: TyS, CaP, and AD. This core 12 includes five of the original six targeted members, only excluding JoM. Nine of the 12 core members were part of the top 15 nodes in degree centrality (table 3), leaving JJ, JH, and WP as less connected yet “core” members. Although JJ’s connection to two members

Table 4. Two-mode and one-mode (categorical and continuous) core/periphery analyses of the 856 co-offending network

2 mode	1 mode	1 mode	1 mode
Categorical	Categorical	Continuous	Continuous
N = 12	N = 13	N = 13	Score (rank)
AD	AD	AD	.302 (3)
TyD	TyD	TyD	.287 (4)
-	BoS	BoS	.156 (12)
JW	JW	JW	.377 (1)
TaS	TaS	TaS	.263 (6)
TyS	TyS	TyS	.271 (5)
DS	DS	DS	.211 (9)
-	CS	CS	.149 (13)
CaP	CaP	CaP	.308 (2)
AS	AS	AS	.215 (8)
-	JoMc	JoMc	.216 (7)
JJ	JJ	JJ	.188 (11)
-	NaD	NaD	.190 (10)
AdS	-	-	-
JH	-	-	-
WP	-	-	-
Fit: .64	Fit: .78	Fit: .85	
Core - mode 2		Gini: .51	
TyS, CaP, AD			

Note. Best fit chosen after 20 separate runs

of the core qualifies him, neither JH or WP had connections that set them apart from the periphery. Those can be seen as classification errors that are almost inevitable in categorical core/periphery analyses (at least within this data). Note that we chose the best fitting solution (.64) after 20 separate runs (same for all models presented in table 4).

The one-mode categorical and continuous analyses each provide the exact same solution, a slightly different one than what we found in the two-mode analysis. The one-mode analysis suggests a core of 13 members, including 9 who were also identified in the 2-mode analysis (CaP, AD, TyD, JW, DS, TyS, TaS, AS, JJ). The four others are BoS, CS, JoMc, and NaD, most of whom had also been identified as key actors from their degree centrality scores (table 3). The continuous core/periphery analysis calculates a “coreness” score which makes it the most attractive solution for our purposes. The suggested number of nodes to be included in the core (13) is based on a fit criterion that chooses the solution with the highest correlation between the coreness scores and an ideal score of a one for every core member and a zero for actors in the periphery (Borgatti and Everett, 1999). This analysis reveals that the targeted six in fact represented 38.5% (5/13) of what the co-offending network analysis suggests is the core 856 gang. Four of the targeted six are included in the top 6 coreness scores: CaP, AD, TyS, and TaS. JW, who ranks number one on this measure, was excluded from the police intervention, as well as TyD who completes the top six. Note that this analysis excludes highly central BoS (Table 3) whose pattern of connection (four total co-offending associations with four different members of the targeted six) place at a disadvantage in an analysis that takes the frequency of associations into account, such as this one. BoS would nonetheless be included in the network-based identification of the core 13 members of the 856 gang.

Discussion

The objective of the current paper was to examine if the decision made by the Langley RCMP to target six of their young local offenders as representing the core of the 856 gang based on manual file reviews was supported an analysis of the co-offending network surrounding those targeted offenders. The results show that:

- 1) Five of the targeted six were central in the network, but no more than at least 10 other, non-targeted offenders;

- 2) If forced to choose a top six to represent the core, only three of the initial targets would make the cut;
- 3) Core/periphery analyses of the co-offending network suggest that the data does exhibit such a structure; 13 offenders would be part of the core, 47 in the periphery. Five of those 13 (38.5%) were identified and targeted by the Langley police.

Identification of the “core” members of a gang may, or may not be an exercise worth undertaking. This exogenously determined core may change daily, may vary greatly based on the type of data used to establish it, may not correspond to what gang members perceive as the core, or the core may be artificial – in fact, it may not exist at all. The question of the utility of classifying gang members into “core” and “peripheral/fringe” members is not likely to have an absolute answer. Fortunately, the question does not have to be resolved subjectively. Social network data, when available, is naturally compatible with those types of questions (Borgatti and Everett, 1999). The results of core/periphery analysis may point to networks where no core is easily identifiable. Alternatively, it may lead to the identification of a core so large that it lacks practical intervention utility (if 80% of the members form a core, why bother choosing?). The bottom line, of course, is the importance of drawing from data to establish a probability, and avoid guesswork.

This is not to suggest that the manual file reviews conducted by the Langley RCMP to identify the core 856 members was not useful. On the contrary, we want to suggest that neither SNA nor manual file reviews, alone, is likely provide a fully satisfactory solution to the gang boundaries problem. This can be illustrated by the seemingly mystery inclusion, by the Langley RCMP, of JoM in the targeted six members. Although the co-offending network labels him as a peripheral member, it may very well be that JoM is simply more successful than others at avoiding detection – much like Morselli’s (2009) Bo-Gars in Montreal. Network data alone, without the benefit of context or node attributes, results in conclusions that are helpful, but sometimes tentative. As emphasized by both Fleisher (2005) and Papachristos (2006), network visibility as measured by centrality need not be automatically associated to a position of leadership or high social status in the network. This is especially the case for official data. Note, however, that five of the six targeted 856 members were found to be in the most central actors in the co-offending network. Clearly, co-offending data is suitable for purposes of understanding the social environment within and around street gangs.

A limitation of our study emerges from the two-mode research design that we adopted. The lack of information on co-offending outside of the targeted six makes our study dependent on those six, failing to provide a truly alternative method to assess the core of the 856 gang. At the same time, this dependence by design was necessary. Indeed, the targeted six was the only place to start. Analyzing any co-offending network near or far of those six offenders could have led to the emergence of different key players or a different core, but there would be little to connect those central actors to the actual 856 gang problem that Langley was facing. Although not perfect, reliance on the targeted six 856 members for network construction allowed us to stay on target given the data available.

Other limitations of this study and their implications have been discussed earlier, including the lack of attribute data on offenders in this co-offending network. Although we relied on both suspected and official co-offending records, drawing on such data is always subjected to a missing data issue that is common in social network studies. Future work should pursue Fleisher's (2005) and Morselli's (2009) efforts in providing systematic comparisons of the results of social network analyses conducted from two or more sets of alternative data (e.g. wiretap v. co-offending data). Criminology historically devoted much research in determining precisely the implications of relying on different sets of data (official records, self-reported delinquency and victimization surveys). No one is surprised, for example, to find that violent crimes are over-represented in official data given their visibility and importance for police priorities, or that offenders are officially charged with fewer accomplices than they had in reality (and would self-report). The pool of SNA-based criminology studies is growing, the data sources are varied, but the implications for interpretation have yet to be made explicit.

References

- Borgatti, S.P. and Halgin, D. (2011). Analyzing Affiliation Networks. In Carrington, P. and Scott, J. (eds) *The Sage Handbook of Social Network Analysis*. Thousand Oaks, CA: Sage Publications.
- Borgatti, S.P. and Everett, M.G. (1997). Network Analysis of 2-mode data. *Social Networks*, 19, 243-269.
- Borgatti, S.P. and Everett, M.G. (1999). Models of Core / Periphery Structures. *Social Networks* 21, 375-395.
- Borgatti, S.P., Everett, M.G., and Freeman, L.C. (2002). UCINET for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies
- Borgatti, S.P. (2002). NetDraw: Graph Visualization Software. Harvard, MA: Analytic Technologies.
- Decker, S. H. (1996). Collective and normative features of gang violence. *Justice Quarterly*, 13, 243-264.
- Faust, K. (1997). Centrality in affiliation networks. *Social Networks*, 19, 157-191.
- Fleisher, M. S. (2005). Fieldwork research and social network analysis. Different methods creating complementary perspectives. *Journal of Contemporary Criminal Justice*, 21, 120-134.
- Maxson, C. (2011). Street Gangs. In: Wilson, J. Q., and Petersilia, J., (Eds.), *Crime and public policy* (pp.158-182). Oxford University Press, New York.
- Morselli, C. (2009). *Inside Criminal Network*. New York : Springer.
- Papachristos, A. V. (2006). Social network analysis and gang research : Theory and methods. In J. F. Short & L. A. Hughes (Eds.) *Studying Youth Gangs* (pp. 99-116). New York: Alta Mira Press.
- Spindler, A., Bouchard, M. (2011). Structure or behaviour? Revisiting gang typologies. *International Criminal Justice Review*. Online First.