Measuring UK Crime Gangs

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***Abstract*—This paper describes the output of a study to tackle the problem of gang-related crime in the UK; we present the intelligence and routinely gathered data available to a UK regional police force, and describe an initial social network analysis of gangs in the Greater Manchester area of the UK between 2000-2006. By applying social network analysis techniques, we attempt to detect the birth of two new gangs based on local features (modularity, cliques) and global features (clustering coefficient). Thus for the future, identifying the changes in these can help us identify the possible birth of new gangs (sub-networks) in the social system. Furthermore, we study the dynamics of these networks globally and locally, and have identified the global characteristics that tell us that they are not random graphs – they are small world graphs – implying that the formation of gangs is not a random event. However, we are not yet able to conclude anything significant about scale-free characteristics due to insufficient sample size.**

I. INTRODUCTION

We present the dynamics of a social network study of gang activity in Greater Manchester, a region in the north of the UK. We use the intelligence gathered by police observations of known gang members and associated criminals. We develop the statistical analysis of network dynamics, combining well-known global topological measures, local motifs and modules [1]–[3]. Network motifs are subgraphs that appear more frequently in a real network than could be statistically expected. At a global level, if these networks of associations exhibit clustering behaviour this indicates the presence of gangs. At a local level, any defined substructures will provide us information about the gang structure. We are interested in modelling the dynamics of the gangs, their development and fragmentation into new gangs, and we hope that the study of the dynamics in such modules will provide information on the structural changes within gangs that lead to birth of new gangs, and predictors of other gang-related behaviour.

Furthermore, we investigate if the networks have scale-free, small-world or other characteristics [3]–[5]; small-world networks are characterised by a diameter that grows logarithmically with their size. One important characteristic of the small-world phenomenon is that each pair of nodes are connected through a relatively small number of steps to a huge network size defined by the total number of nodes. Scale-free structures consists of many nodes with low degrees and a few hubs with high degrees [1], [2], [6]. If the offender networks can be classified into either (or both) of these categories (or other known network types), then this provides not only insight into the dynamics of the gang network, but also operational uses; for instance, network disruption/destruction strategies, nodes/offenders to monitor, and so on.

II. PROBLEM DESCRIPTION AND DATA

Numerous shootings – both fatal and non-fatal – have taken place over the years as the the Pepperhill, Gooch, Doddington and Longsight Crew gangs (see Table I) have clashed over drug territories and other disputes. Many of these gun fire exchanges were on public streets, some were planned acts and some were spontaneous events.

Gang label	Gang Name	Formation
A	Gooch	1990s
B	Doddington/Pepperhill	1990s
C	Longsight Crew	c.2001
D	Rusholme Crew Gangsters	c.2004

Table I. GANG NAMES AND APPROXIMATE DATES OF FORMATION.

In 2001, a new approach to tackling gun crime began to develop with police working more closely with the local community and other agencies. The Manchester Multi-Agency Gang Strategy (MMAGS), a multi-agency approach to tackling gun crime and detering young people from entering into a gang/gun culture was initiated as a result of a UK Home Office report [7]. The report concludes that about 60 per cent of shootings are thought to gang-related, with violence in general, and gun violence and fatal shootings inparticular are concentrated in specific small areas of South Manchester, and that gangs in South Manchester are loosely turf-based.

The geographical proximity between Gangs A and B is hundreds of meters, literally a few streets away from each other. Gangs A and B show a negative attitude towards each other, often resulting in 'tit-for-tat' gun crimes. The alignment between Gangs A and D is possibly because of a mutual rivalry with B, while the positive alignment of B with C is because A has encroached on C's 'territory' for drug sales. Agreeing strongly with the Home Office report [7] we find: 38% (n=162) of all serious crimes occurring within 1 km radius (of gang locations) and 63% of all serious crimes occur within 2 km, and 53% (n=9) of murders are within 3 km; 38% (n=34) of attempted murders are within 1 km and 63% within 2 km; and, 33% (n=17) of serious woundings are within 1 km and 48% are within 2 km.

III. POLICE DATABASES

The database used for this analysis included the list of associates for each gang member, with fields such as unique identifiers for each offender, date of birth, relationship between the offenders, ethnic origin, reason reported and date of occurrence.

The network links available are quite different to other existing work with networks of burglars or retail fraudsters [8], [9]). These link types are: *Accomplice*; *Brother-Brother*; *Boyfriend*; *Brother*; *Sister*; *Charged with*; *Child*; *Cohabitant*; *Foster child*; *Foster parent*; *Friend*; *Girlfriend*; *Guardian*; *Other*; *Parent*; *Relative*; *Spouse*; *Sister-Sister*; *Ward*; *Gay Boyfriend*; and *Gay Girlfriend*.

IV. Identifying community structure

In order to investigate community structure we removed any nodes with less than six connections (i.e. degree 6); Figure 1 shows data from 2002, with the well-established Gangs A and B, and also the newly formed Gang C (in 2001). The Gangs A, B, and C are highly interconnected, with Figure 1 also showing the 'go-betweens', labelled as *ab** and *bc**. Individuals who are only connected to one gang, and who are highly connected within themselves, are labelled *a** and *b**. In this way it is easier to see the communities.

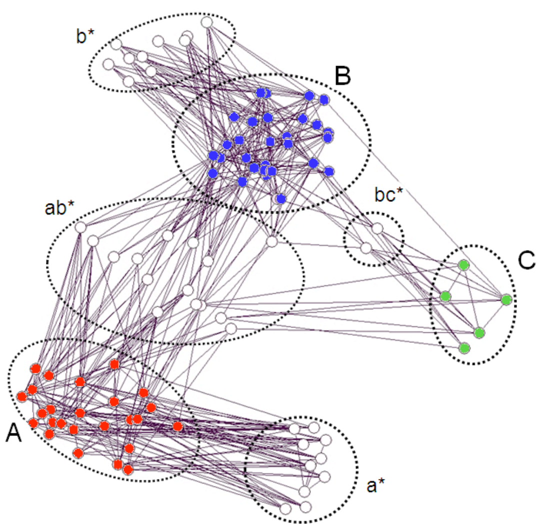

Figure 1. Link reduction, showing Gangs A and B and emergence of Gang C (for 2002). This also illustrates the large amount of non-gang members who are associated with individual gangs (*a**, *b**) or who are intermediaries (*ab**, *bc**).

V. Network characterisation

A series of experiments were carried out to determine how the gang networks compare with well-known networks, for example scale-free and small-world networks.

A. Small-world networks

Table II presents the clustering coefficient [10] (CC) for each individual year, alongside the node and edge counts and various other measures to describe the network. For any simple connected graph G with at least two vertices, the clustering coefficient (1-neighbourhood) [10] measures the extent to which vertices linked to any given vertex v are also linked to each other. Or in other words, are the friends of my friends also my friends? This is 1-neighbourhood clustering. The clustering coefficient 2-neighbourhood is a less stringent condition, and states: of the friends of my friends, are they linked to me by other friends?

The links presented in Table II are cumulative; that is, the links and nodes for 2002 include not only the new links and nodes for 2002, but also those for 2001 and 2000.

Measure	2000	2001	2002	2003	2004	2005	2006
Number of nodes (n)	1095	1295	1487	1752	2090	2229	2408
1/n	0.00091	0.00077	0.00067	0.00057	0.00048	0.00045	0.00042
4/n	0.00365	0.00309	0.00269	0.00228	0.00191	0.00180	0.00166
log(n)	6.999	7.166	7.305	7.469	7.645	7.709	7.787
log(log(n))	1.95	1.97	1.99	2.01	2.03	2.04	2.05
Number of links	1565	1903	2295	2844	3540	3872	4265
Total possible links	598965	837865	1104841	1533876	2183005	2483106	2898028
Diameter	12	14	11	11	14	12	13
Average path length	4.85	4.82	4.68	4.57	4.86	4.78	4.70
Density	0.00261	0.00227	0.00208	0.00185	0.00162	0.00156	0.00147
Betweenness	0.107	0.117	0.172	0.205	0.146	0.102	0.100
CC (cumulative)	0.47	0.48	0.47	0.46	0.49	0.55	0.56
CC (per year)	0.24	0.57	0.34	0.15	0.62	0.25	0.30

Table II. Network measures for 2000-2006. Clustering coefficients are always greater than 4/n. Average path lengths are always less than log(n).

Table III shows the same network measures, but this time the data has been sliced into the members of the Gangs A, B, C and D.

Measure	A	B	C	D
Number of nodes (n)	859	617	431	513
1/n	0.00116	0.00162	0.00232	0.00195
4/n	0.00466	0.00648	0.00928	0.00780
log(n)	6.76	6.42	6.07	6.24
log(log(n))	1.91	1.86	1.80	1.83
Number of links	844	1047	602	707
Total possible links	368511	190036	92665	249571
Diameter	7	5	6	7
Average path length	3.61	3.38	3.37	4.11
Density	0.00396	0.00550	0.00648	0.00537
Closeness	0.302	0.298	0.393	0.305
Betweenness	0.185	0.179	0.350	0.239
CC	0.16	0.19	0.15	0.12

Table III. Network measures for Gangs A, B, C, D. CC is the average clustering coefficient from [10], considering only 1-neighbourhood.

A small-world network has both local connectivity and global reach [10], and is a simple connected graph G exhibiting two properties:

1) Small characteristic path length: the presence of short-cut connections between some vertices results in a small characteristic path length $L(G)$.
2) Large clustering coefficient: each vertex of G is linked to a relatively well-connected set of neighbouring vertices, resulting in a large value for the clustering coefficient $C(G)$.

To determine whether our network is a random one or is small-world, we can test whether or not it has exponential k-connectivity distribution. We do not observe this in the data, however, we do see large clustering coefficients, and the average path lengths are always less than *log(n)*. Based upon these two criteria we can still conclude that our networks have small-world characteristics.

B. Scale-free networks

This section also refers to the preceding tables, where we find a mixture of evidence for and against the case for scale-free networks.

Plotting the clustering coefficient as a function of the number of nodes n, should follow the power-law distribution for scale-free networks (see later experiments), with the clustering coefficient being roughly four times larger than random networks [6]. The value of the clustering coefficient for a random networks will be *1/n*. In this way we are able to compare the values of *4/n* against CC in Tables II and III. As the cumulative links increase from 2000 to 2006, the value of CC generally increases (with the number of nodes n) and is always significantly higher than the values of *4/n*. Each of the gang values for CC are also significantly higher than would be expected in a random network.

The diameter of the network (longest path length) should be approximately *log(log(n))* for scale-free networks. In both cases (for the gangs and the years) the real values are significantly higher than would be expected for a scale-free network. The average path length should be approximately *log(n)* for scale-free networks. For both the 'years' and 'gangs' data it was actually smaller than *log(n)*, indicating scale-free networks.

The statistics on degree centrality were low, indicating that there is no group leader. As we know when Gangs C and D are formed (2001 and 2004 respectively), it is interesting to note that the characteristic of the networks at this time are that the betweeness centralisation reaches 0.2. It is necessary to compare the closeness and betweenness averages for each gang against the value for the overall network.

C. Power law investigation

Our initial power law investigations used a log-log plot and R^2 values, and these all produced α values within this typical range (between 2 and 2.5). However being roughly straight on a log-log plot is a necessary but not sufficient condition for power-law behaviour [11], and that there are problems (bias and inaccuracy) with fitting to the power-law distribution using graphical methods based on linear fit on the log-log scale.

We therefore proceeded to use maximum likelihood estimation (MLE), which is a far more robust method for estimating the scaling exponent [11], [12]. We report the maximum likelihood estimate of the scaling exponent (α), the estimate of the lower bound of the power-law ($xmin$).

By optimising the Kolmogorov-Smirnov goodness-of-fit statistic, we can use a *goodness of fit* to estimate where the empirically-best scaling region begins [11]. Given an observed data set and a hypothesised power-law distribution from which the data are drawn, we can then test whether our hypothesis is a plausible one using the goodness-of-fit test (the Kolmogorov-Smirnov statistic), given the data, and generate a p-value that quantifies the plausibility of the hypothesis.

Employing the Kolmogorov-Smirnov test we are able to choose among the hypotheses that:

- *H0*: the data follow a specified distribution;
- *Ha*: the data do not follow the specified distribution.

We did not use Vuong's test to check for alternative distributions (non-power-law distributions) which could have produced the data. Instead, because our sample sizes are small (i.e., < 100), we explicitly used an experimental finite-size correction, as recommended by [11].

Figure 2 shows our results for our network between 2000-2006. In all cases the exponent α is less than 2. Only when the power-law exponent is in the range $2--3$ do the hubs tend to connect to form a single cohesive hierarchy [13]. The goodness-of-fit (gof) and p-values however are significant. Even though the p-values are above 0.1 (arbitrary threshold level), we err on the side of caution because of the low α value and the small sample size. When n is small, meaning $n \leq 100$, we cannot rule out the power-law hypothesis [11]. It is possible, for small values of n, that the empirical distribution will follow a power law closely, and hence that the p-value will be large, even when the power law is the wrong model for the data [11].

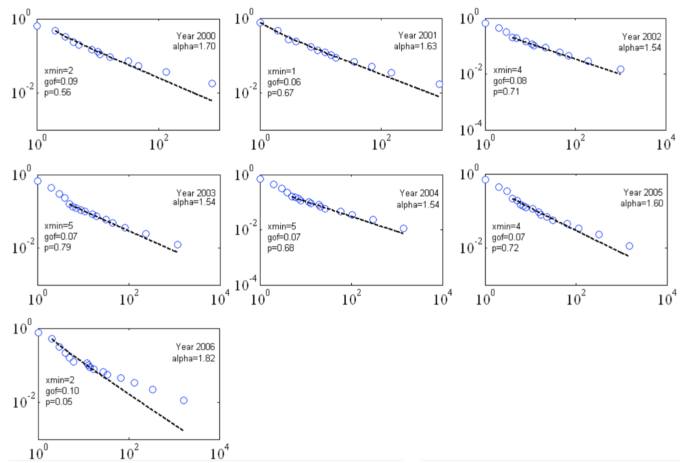

Figure 2. Power law investigations. A power law is fitted to each years data and various statistics calculated: the exponent alpha, xmin, goodness-of-fit (gof) and p-value.

Table IV shows our results for the power law exponent for the different gangs against years. The case is similar in that there are significant gof and p-values, however in nearly all cases the exponent is less than 2, and again we did not test for alternate explanatory distributions, satisfied (operationally) that the the tail was heavy in all cases, indicating the presence of very well connected offenders.

Gang	1999	2000	2001	2002	2003	2004	2005	2006	2007
A	**2.65**	1.47	1.00	**1.91**	1.07	0.10	0.94	0.77	0.74
B	**2.95**	1.44	**3.64**	**1.88**	1.36	0.09	0.97	0.63	0.51
C	0.27	0.24	0.17	0.32	0.38	0.02	0.46	0.36	0.32
D	1.26	0.76	0.56	0.69	1.14	0.03	1.21	0.81	0.65

Table IV. POWER LAW EXPONENTS FOR GANGS, AGAINST YEARS (SIGNIFICANT RESULTS ARE SHOWN IN BOLD).

Based on these experiments we are therefore unable to comment whether the networks possessing scale-free characteristics, however we can conclude that we have small-world networks, since consistently there are larger clustering coefficients and shorter path lengths compared to a random network with same number of gang members. This means two things for our system:

- The smaller path length means that the criminal activity (contagion) spreads more easily in this network than in a random network.

- Larger clustering coefficient means that contacts of contacts are treated as contacts as well.

D. Emergence of gangs

We might see changes in the path length and clustering coefficients from 2000 to 2005, indications of how the gangs have become more closely knit or are splitting apart. By examining annual links for 2001 and 2004, we might predict that the cumulative links decrease and the annual links increase, just before/as a gang forms, then both values increase afterwards as everyone becomes linked together. This is not the case, and neither are we able to see any meaningful behaviour in these data.

Figure 3 shows the clustering coefficients for each gang and against years. In Table 3 the CC value of each gang dips at 2004. What this may indicate is clustering due to non-gang members (from Figure 1, offenders who are connected to gang members: *a**, *b**, *bc** and *ab**) and less clustering that previous years between members of gangs themselves. There is also a significant peak in clustering during 2001 for Gang B, whereas all other gangs suffer a decrease in clustering.

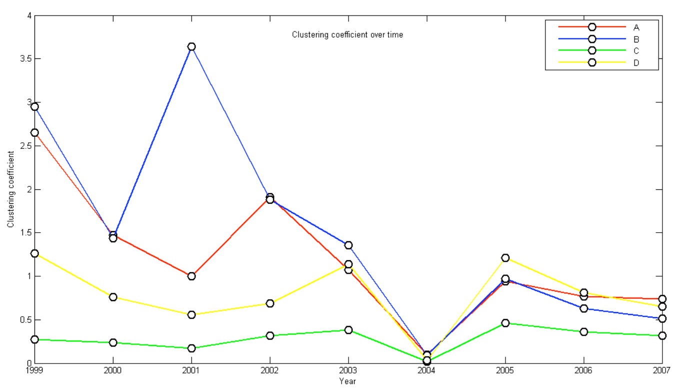

Figure 3. Per year clustering coefficients for each gang. Gang C was formed in 2001, Gang D in 2004.

VI. Discussion

The model of two rival sets of gangs is potentially a misrepresentation of the much more complex sets of smaller cliques and fluid changes within the larger gang structures. However, the four gangs discussed do exist, and are the main gangs; what is not possible is a high degree of exactitude.

We require a much better analysis of link types, developed a model where individuals learn about crime opportunities by interacting with other peers; for instance whether weak ties play an important role in explaining criminal activities [14], especially gang homicide [15]. The theoretical predictions of the model are confirmed by the empirical analysis since they find that weak ties, as measured by friends of friends, have a positive impact on criminal activities.

Furthermore, for 2001 and 2004, it would be interesting to examine the kinds of links within each gang which split apart.

VII. Conclusions

The work presented in this paper contains our initial findings about the offender/gang networks in Manchester in the UK, using network analysis. The uses of this technology in an operational context are significant. Even using the networks merely as visual representations of otherwise cognitively unmanageable data contained in spreadsheets and databases is operationally very useful, for knowledge sharing and training, and identifying key offenders. When further pre-processing is carried out, and the quality of the data collection process is improved, there will be sigificant future work available with this dataset.

The police crime recording database is routinely gathered and available for analysis. The additional databases of histories and associates of gang offenders are routinely gathered by the UK's National Crime Agency [1], who investigate gang and gun-related crimes. These data sources are potential rich sources of information for computer science technologies to deliver crime prevention and detection decision support systems.

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