Criminal Networks and Spatial Density

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1. INTRODUCTION

The authors work in this area [2,6,7], in collaboration with West Midlands Police (WMP), is with the high volume crime of Burglary from Dwelling Houses (BDH). The presented work involves the brokerage metric from social network analysis combined with a geographical component (not present in other approaches) to add to the interpretation of the network and its key players. Our work builds upon several years of experimentation using forensic psychology guided exploratory techniques from artificial intelligence, statistics and spatial statistics.

Social network analysis (SNA) technologies [9] are an established methodology within the social sciences. *Local centrality* is defined as the vertex *degree*, the amount of links in or out (or both) from that vertex. A vertex is *globally central* (*closeness*) if it lies at short distances from many other vertices. *Betweenness* measures the extent to which a particular point lies 'between' the various other points in the graph: a point of relatively low degree may play an important 'intermediary' role and so be very central to the network. Betweenness measures the extent to which an agent can play the part of a 'broker' or 'gatekeeper' with a potential for control over others, able to monitor the information flow through the network, and having the best visibility into what is happening in the network [4].

2. BDH ARREST DATA NETWORKS

The networks and geographical outputs presented below are derived from 342 offenders who committed 1121 crimes (representing the time period 1997-2001). The network links are based upon who are the co-defendants arrested for a particular crime and the geographical location of that offence, representing a significant departure from previous methodologies in that links are on the basis of an established (albeit not proven in court) co-defendant relationship.

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Other approaches, such as using mobile phone records or police intelligence, employ such data to infer a criminal relationship. Here, there is little ambiguity. One advantage of this approach is that all police forces maintain arrest data about individuals and crime location information. The forces do not have to mount expensive surveillance operations or access phone records in order to apply the approach described here.

The following are results achieved from conducting experiments with the PAJEK software [1], using the SNA methods of network reduction and brokerage. Some form of reduction plays a part in the investigation of most networks, primarily by the *degree* of a node – i.e. the number of links in which a node is involved. In our experiments the original network was reduced in size to 145 nodes (degree >4). The brokerage experiments resulted in many small sub-networks of size 2, 3 or 4 nodes, and two much larger sub-networks, which are presented in the figures 1 and 2.

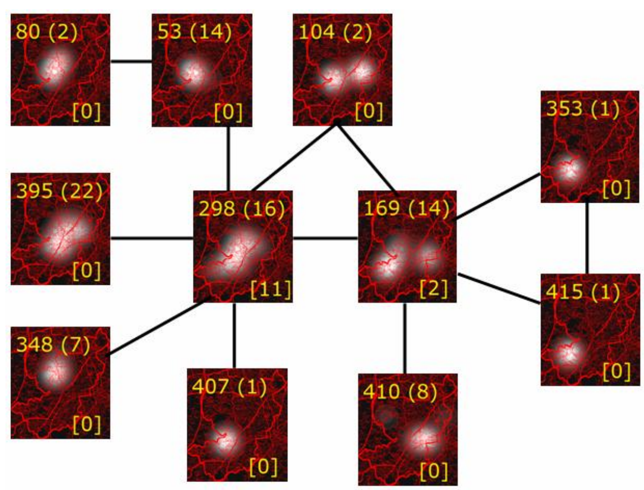

Figure 1. Brokerage analysis: sub-network 1.

The nodes are overlaid with the offender activity represented as *kernel density estimations,* or smoothing that results in crime 'contour' maps (described in: [6]). Comments on these figures use the orientations 'northwest', 'southwest' etc in relation to the centre point of the figures. The top-left numbers are unique offender identifiers, with the total number of crimes in brackets.

The bottom-right number is the brokerage value. Figure 1 shows offender #298 receiving the highest 'brokerage' value of 11, higher than #169 by merit of being a 'gatekeeper' to a greater number of vertices. Offender #104 receives a very low value, providing no 'new information' as #298 and #169 are already linked. Figure 2 again illustrates the workings of the brokerage algorithm, with offender #171 receiving the highest value.

It can be quite clearly seen that the brokerage model accurately reflects offender #298 connecting the centre and northwest areas (#80, #53, #395, #348) with the southwest areas (#407). Also, the total offences that can be uniquely reached through #298 number 46, in comparison to those that can be uniquely reached through #169 numbering 10. This would agree with #298 receiving a higher brokerage value than #169.

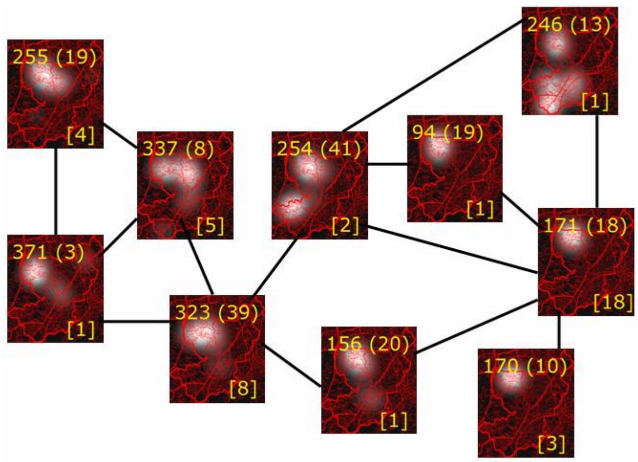

Figure 2. Brokerage analysis: sub-network 2.

However, what is not reflected in the model is that we want #169 to receive a value higher than their current brokerage value as they are gatekeeper to #410 with 8 crimes in the southeast area, a unique offender by right of area of operation. Similarly #169 is gatekeeper to a much wider geographic range of offenders: #104 in the east; #353 and #415 in the southwest area; and, #410 in the southeast. Offender #298's connections only lie within the centre and slightly to the northwest. We then want the weightings to be taken account in the brokerage calculation (reflecting the number of crimes committed between offenders), and also that the notion of criminal range [5] was given a suitable emphasis.

An analysis of Figure 2 again demonstrates that it does not reflect important factors we would like incorporated. It is clearly not easy to justify #171 receiving the highest brokerage value. Other equally interesting offenders are: #323 because of the high number of crimes; #254 because of crimes number and that the members operate in the northwest and also in the southwest; and, #246 because of the large area of activity of this group.

3. CONCLUSIONS

It is important to note that because the original network has been reduced to nearly half its size, nodes that appear to have degree 1 may in fact have several other links, and be reachable from other nodes. This however would also be the case with a 'full' arrest dataset being used – many crimes are unsolved, and many relationships will not be reflected in the data.

A further concern is that the outputs are generated at the end of the time frame of criminal activity, confounding the interpretation of the relationships between the key players in a network and their spread of criminal activities. For example, offender #171 is a key player in figure 2 and linked to #246. However, their respective patterns of offending are very different. Only by examining the evolution of their respective patterns over time, can we even begin to consider if #246's greater spread was associated with, for example, the arrest of #171, or whether #246 has always been a 'commuter' and 'maurades' [see 8] only when #171 is around. With temporal and geographical knowledge we can make some assertions about whether #246's activities are due to criminal drift, 'foraging' [3] or #171's absence. We can also say much more about the role of #171 in respect to links to others in the network. Furthermore, we can say much more about the value (or otherwise) of the integration of geographical and spatial data and it is at this point, that policing value is maximised.

4. REFERENCES

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