Network Analysis of a London Street Gang*

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It is well known that deviance among youth rarely occurs by a single individual. Even in situations where delinquency occurs by a single individual, it has been shown that this rarely occurs without an outside influence[1]. This research focuses on the ways in which youth choose who to co-offend with. The focus is split between the processes of selecting a co-offender for petty crimes, serious crimes, and all crimes. This is done through an analysis of a co-offending network in a London Street gang. It is found that common birthplace is the attribute which produces the most assortativity, different individuals play central roles within the network for different levels of crime, and co-offending relationships can be predicted with up to 85% accuracy.

Introduction

Co-offending is the act of two or more individuals committing a crime together. It has been shown that delinquency among youth most commonly occurs in situations where the deviant individuals do not act alone or are heavily influenced by outside actors.[1] The ability to understand and predict how individuals choose who to co-offend with may allow government and law enforcement to inhibit further criminal activity. It has been theorized that gang members learn to become criminal because, upon joining the gang, they are put into a social environment which rejects traditional social norms. This environment is made of influential individuals which guide new members' beliefs and values.[2] This research is aimed at transforming traditional qualitative social theories into quantitative measures through analysis of a co-offending network representative of a London street gang. To this end, the following hypotheses are tested:

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*Code can be accessed at https://github.com/erparks/Network-Analysis/tree/master/Project
Data can be found at https://sites.google.com/site/ucinetsoftware/datasets/covert-networks/londongang
[1]Abbott, E., & Breckinridge, S. (1917) The Delinquent Child and The Home 34-35.
[2] Sutherland, E. (1947). *Principles of Criminology.* Philadelphia, Pennsylvania. J. B. Lippincott Co.

Hypothesis 1: As shown in previous research[3], shared ethnicity will be the most significant predictor of co-offending.

Hypothesis 2: There will be different individuals who are more important to the structure of the gang with respect to severity of criminal activity.

Hypothesis 3: Co-offending relationships between two individuals will be predictable using only information about the two individual's existing co-offending relationships.

To test these hypotheses, analysis of the networks assortativity is conducted to determine if there are common attributes between individuals who choose to co-offend together as hypothesis 1 predicts. The network structure is analyzed through node importance measures to determine if there are certain individuals who are more central to the dynamics of the network as hypothesis 2 predicts. Lastly, three edge prediction algorithms are applied to the network to investigate hypothesis 3.

Data

The data is collected from 2005 to 2009 and represents a "durable, street-oriented youth group whose involvement in illegal activity is part of their group identity". The gang operates in a lower socio-economic status inner London borough and every member is male[4]. The data is collected from police arrest records of confirmed gang members. Individuals are considered confirmed gang members if they meet at least two of the following criteria: admitted gang membership, been vouched for by another gang member, been arrested with a gang member, displays a gang tattoo or brand, wears clothing or symbols intended to identify with the gang, appeared in a photograph with a gang member engaging in gang-related activity, or communicates with a confirmed gang member to facilitate gang-related activity. The data contains demographic information for each individual including age, birthplace, arrests, convictions, whether the individual has spent time in prison, and music taste. This research focuses on 54 individuals and their co-offending relationships.

During all stages of analysis, the data is interpreted as a network with individual gang members represented as nodes and a link connecting two nodes if the two gang members have been arrested together. Three criminal networks are created from the data, one which contains links representing only petty crimes (92 links), one which contains links representing only serious crimes

[3] Grund, T. & Densley J. (2014). Ethnic Homophily and Triad Closure: Mapping Internal Gang Structure Using Exponential Random Graph Models. Journal of Contemporary Criminal Justice.

[4] Klein, M., & Maxson, C. (2006). Street gang patterns and policies. New York, NY: Oxford University Press.

(41 links), and one which contains all links representing both petty and serious crimes (133 links). Each stage of analysis is applied to each of the three networks.

Network Assortativity

Analysis

According to social learning theory, one learns social norms via observation.[5] It follows that individuals are more likely to be around people of their own ethnicity, and therefore be more likely to learn social norms from people of their own ethnicity. Given that criminal activity has occurred, as is documented through the network, social learning theory would suggest that the offenders have learned the behavior from those around them. Because of these ideas, it is expected that the birthplace attribute will show the highest levels of homophily.

Results

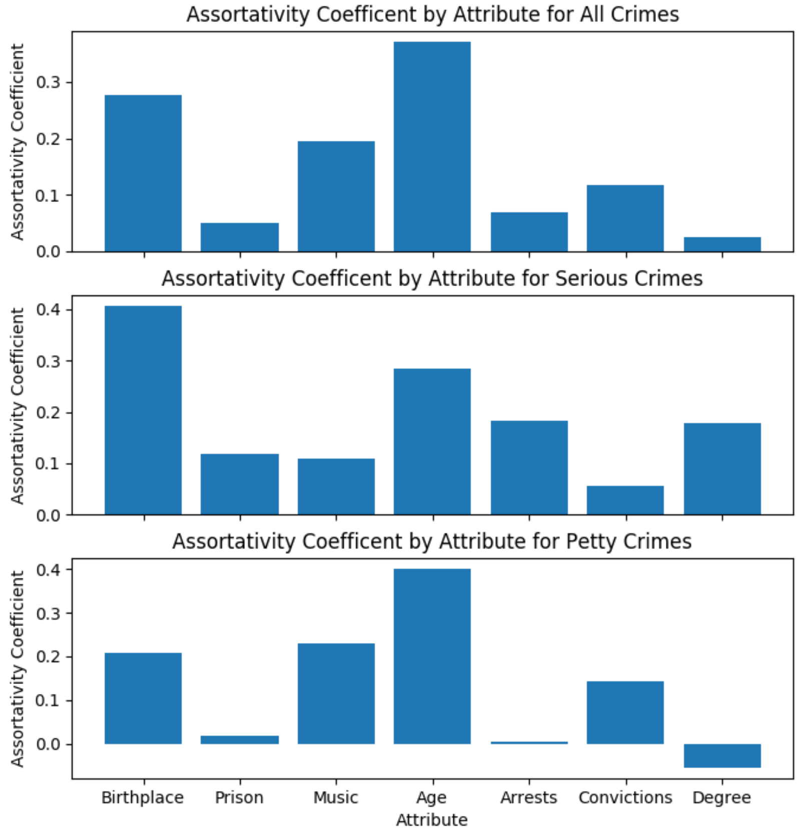
Figure 1 shows that age and music taste are the attributes with the highest assortativity in the networks made of links representing petty crimes. There is evidence that music taste is a function of the environment in which an individual resides.[6] Correlation across music taste and age gives reason to believe that co-offenders come from similar social circles. The petty co-offending network also exhibits disassortativity with respect to degree. This suggests that less experienced criminals are committing petty crimes with more experienced criminals. This is a side effect of new members learning criminal behaviors from existing gang members. Learning criminal behavior from your social circle aligns with Sutherland's differential association theory that states individuals learn behaviors from their social environment.[2] Differential Association asserts that co-offending relationships would form between new gang members and existing, influential criminals. Co-offender selection appears to operate differently for serious crimes, however. Correlation across birthplace is doubled for serious crimes. Shared birthplace may indicate a stronger bond between co-offenders that is required to trust an accomplice when the stakes are higher. Assortativity with respect to number of co-offending relationships (degree) also increases significantly. Serious crime co-offender selection follows the reasoning presented by Flashman and Gambetta[7], which states that criminals look for trustworthiness when selecting co-offenders. Sharing a common ethnicity may lend more trust to the relationship.

[5] Bandura, A. (1971). Social Learning Theory. General Learning Corporation.

[6] McDermott, J. et al. (2016). Indifference to dissonance in native Amazonians reveals cultural variation in music perception. *Nature*, 535, pp. 547–550.

[7] Flashman, J & Gambetta, D. (2014). Thick as thieves: Homophily and trust among deviants. *Rationality and Society*, 26(1). pp. 3-45.

Figure 1 - Assortativity Coefficients by Crime Severity



Increased degree assortativity is predicted as a signal of a need for trust by Flashman and Gambetta who states that criminals seek to co-offend with individuals with whom they can share compromising secrets.

Figure 1 shows that Hypothesis 1 and the previous research[3] is supported by the network representing all documented co-offending relationships and the network representing purely serious co-offending relationships. In the case of petty crimes, however, the process of co-offender selection appears to be under greater influence from non-ethnicity-based factors.

Network Structure

Analysis

To measure structural importance of individuals in the gang, harmonic, betweenness, and degree centrality is measured for each node as well as each node's dynamical importance.

Dynamical importance measures the effect of the node on the largest eigenvalue of the network's adjacency matrix.

It has been shown that a node with low degree can still have a large effect on the dynamics of a network.[8] Betweenness

[8] Restrepo, J., Ott E., & Hunt, B. (2006) Characterizing the dynamical importance of network nodes and links. Phys. Rev. Lett. 97, 094102.

centrality is measured to quantify the degree to which the individual provides the closest connection between gang members. This is hypothesized to be important because an individual with high betweenness centrality plays a crucial role in making introductions within the gang and providing opportunities for new co-offending relationships. Harmonic centrality is measured to understand how close each individual is to the average individual. This would imply that an individual with high harmonic centrality would have wide spread influence over the network. Degree centrality is measured to determine if influence over the network is a function of number of co-offenders. A configuration model is used to as a null model to compare the values of the structural importance measures to random, given the degree sequence. A configuration model is used to determine whether an individual's influence over the network is a function of the number of co-offending relationships they have (equal to their degree in the network).

Results

In Table 3, Table 2, and Table 1 we see that the most structurally and dynamically important individuals for petty and serious crimes are different individuals. This is evidence that there exist two tiers of criminality within the gang. This is important because it may affect how law enforcement chooses to apply their focus when disrupting gang activity. The existence of two tiers of criminality also supports the idea that there are different processes for co-offender selection occurring with respect to severity of the crime.

There are certain individuals who are more important to the tier of petty offenders. As discussed in the results of the assortativity analysis, these individuals are more influential in shaping the norms of new members and creating new members. Removing these individuals such as the man represented as node 9 may have a large effect on the gang's influence over new members. Node 9, however, as seen in Table 2, does not appear in the top 10 for any structural or dynamic measure in the serious crime network which suggests that the effort to remove node 9 would have little effect on the gangs more heinous crimes.

There are also individuals who only play a central role within the serious crimes graph. Should law enforcement focus on removing these individuals from the gang, it would have a different effect on the functionality of the gang. Node 4, for example, appears to play an important role in the gang's serious criminal activity but not in the gang's petty criminal activity. Focusing effort to remove node 4 may affect the gang's tendency toward serious crimes but make little difference on the number of new individuals joining the gang.

Figure 2, Figure 3, and Figure 4 show the difference between the importance measures of the nodes in the empirical graph and the null model. The null model used is a configuration model to determine if the importance of nodes explained by their degree or their position in the network. When compared

Table 3 - Node Centralities for All Crimes

Dynamical Importance	Harmonic Centrality	Betweenness Centrality	Degree Centrality
(1, 0.0864)	(1, 0.5289)	(17, 0.1338)	(13, 15)
(2, 0.0843)	(13, 0.5258)	(13, 0.1273)	(1, 13)
(9, 0.0814)	(9, 0.5195)	(18, 0.1177)	(2, 13)
(8, 0.0634)	(2, 0.5101)	(1, 0.1009)	(9, 13)
(22, 0.06)	(8, 0.4975)	(22, 0.0999)	(22, 12)
(13, 0.0579)	(22, 0.4903)	(9, 0.0834)	(8, 11)
(5, 0.0458)	(5, 0.4849)	(2, 0.0816)	(0, 9)
(3, 0.0421)	(3, 0.4802)	(19, 0.0689)	(3, 9)
(0, 0.0384)	(4, 0.4645)	(42, 0.0675)	(5, 9)
(21, 0.0352)	(0, 0.4597)	(41, 0.0641)	(4, 8)

Table 2 - Node Centralities for Serious Crimes

Dynamical Importance	Harmonic Centrality	Betweenness Centrality	Degree Centrality
(13, 0.2221)	(2, 0.2116)	(0, 0.0951)	(13, 7)
(2, 0.2218)	(13, 0.2094)	(2, 0.0933)	(2, 6)
(4, 0.1994)	(4, 0.1827)	(7, 0.0871)	(22, 6)
(3, 0.164)	(1, 0.1811)	(21, 0.0697)	(4, 5)
(5, 0.164)	(22, 0.181)	(1, 0.0522)	(3, 4)
(1, 0.0443)	(0, 0.1764)	(22, 0.0475)	(5, 4)
(12, 0.0391)	(7, 0.1745)	(28, 0.0428)	(28, 4)
(14, 0.011)	(3, 0.1733)	(13, 0.0294)	(0, 3)
(7, 0.0099)	(5, 0.1733)	(10, 0.0152)	(1, 3)
(28, 0.0027)	(21, 0.1701)	(8, 0.0062)	(8, 3)

Table 1 - Node Centralities for Petty Crimes

Dynamical Importance	Harmonic Centrality	Betweenness Centrality	Degree Centrality
(9, 0.1509)	(9, 0.4635)	(1, 0.1699)	(9, 11)
(1, 0.0824)	(1, 0.4629)	(17, 0.1388)	(1, 10)
(8, 0.0807)	(8, 0.4164)	(9, 0.1292)	(8, 8)
(6, 0.0608)	(19, 0.4063)	(18, 0.1037)	(13, 8)
(30, 0.057)	(0, 0.3991)	(19, 0.0958)	(2, 7)
(0, 0.0548)	(2, 0.3912)	(5, 0.0739)	(17, 7)
(19, 0.0475)	(17, 0.3868)	(50, 0.0718)	(0, 6)
(7, 0.0471)	(22, 0.3833)	(2, 0.0707)	(6, 6)
(2, 0.0385)	(5, 0.3827)	(53, 0.069)	(19, 6)
(21, 0.0351)	(21, 0.3797)	(42, 0.0673)	(22, 6)

Figure 2 - Comparison to Null Model for Network of All Crimes

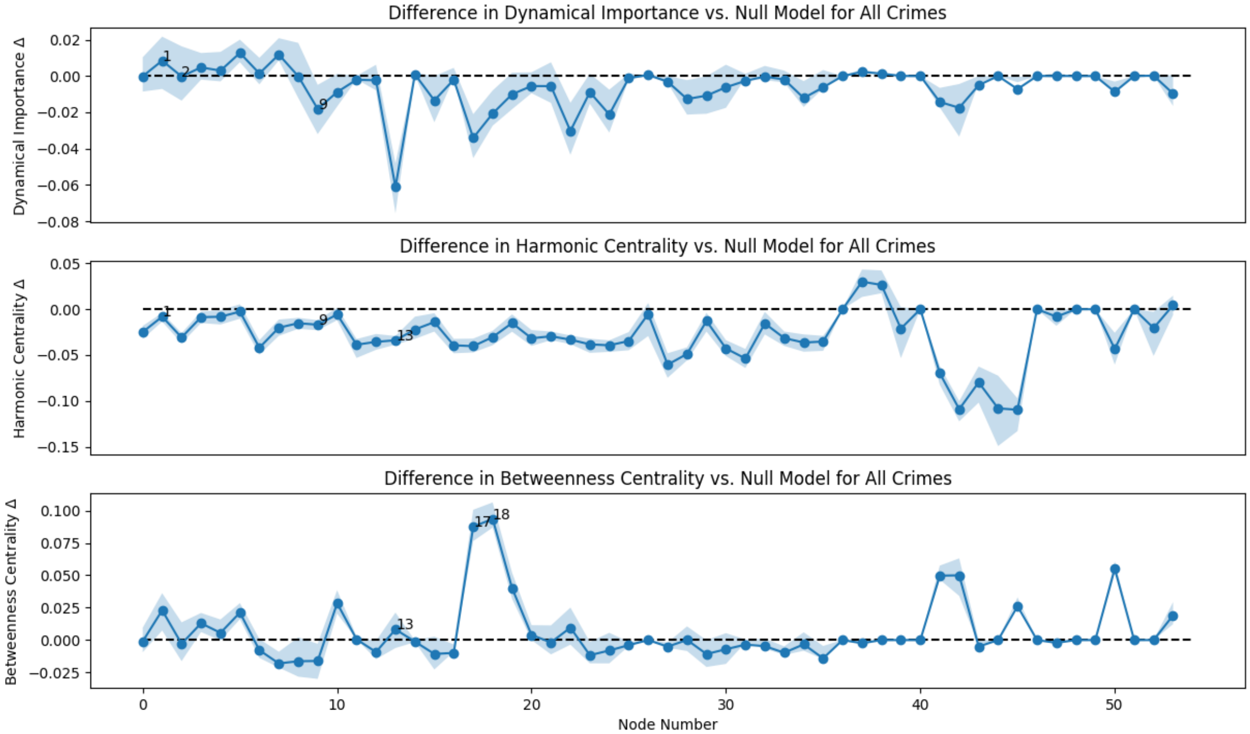


Figure 3 - Comparison to Null Model for Network of Serious Crimes

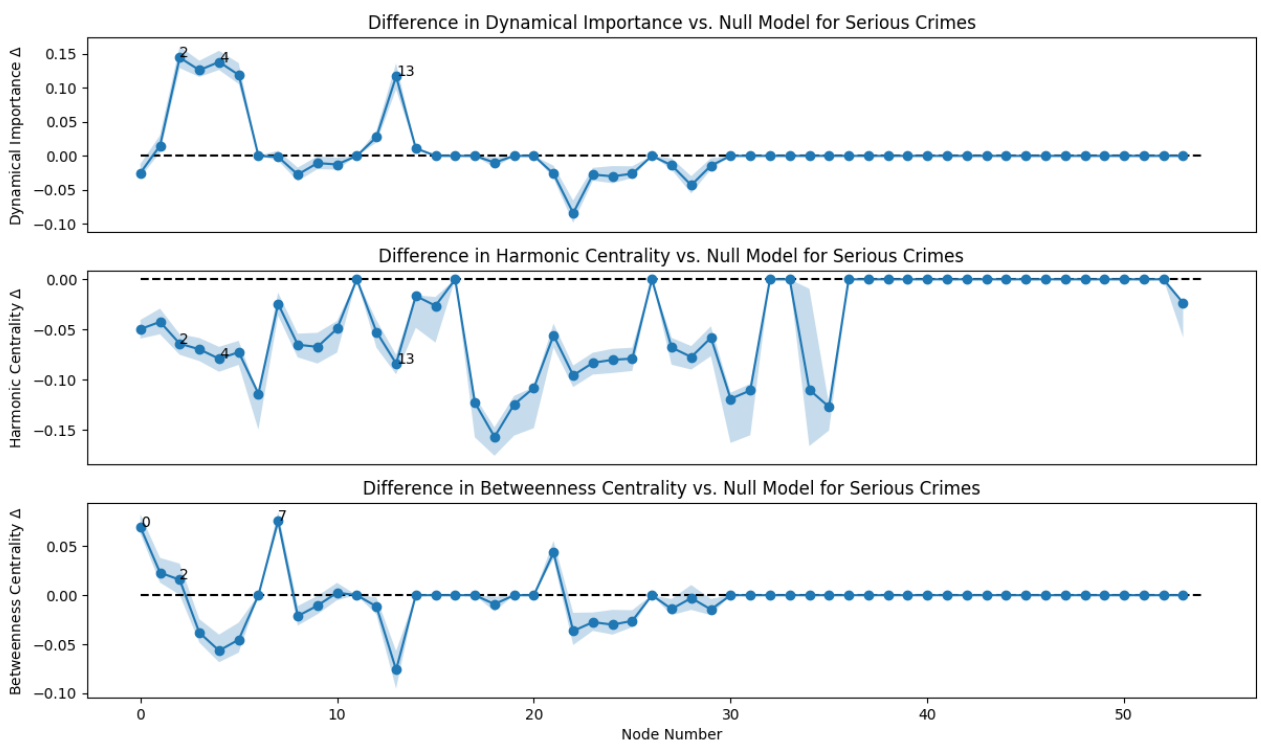
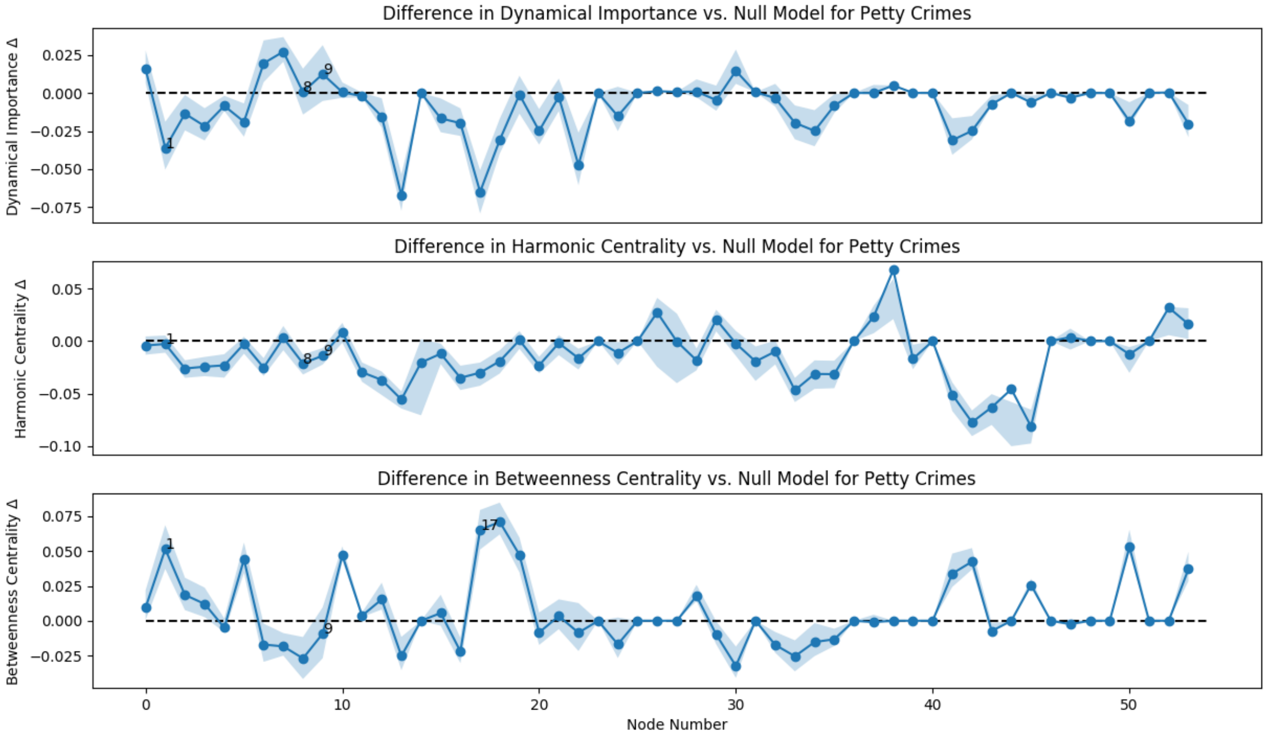


Figure 4 - Comparison to Null Model for Network of Petty Crimes



to the null model, there is little difference in structural or dynamical importance. This aligns with Table 3, Table 2, and Table 1 which show that the nodes with the highest degree also tend to have the highest structural or dynamical importance. The lack of difference from the null model indicates that the importance of individuals in the gang is explained by the number of co-offending relationships they have. Hypothesis 2 is supported as Table 3, Table 2, and Table 1 show that the most important nodes to the graphs structure and dynamics differ between the serious and petty crime networks.

Edge Prediction

Analysis

Three edge prediction algorithms are applied to the three networks in attempt to use the structure of the network to better understand the underlying system of co-offender selection. It follows that the algorithm with the highest accuracy would best explain how individuals chose with whom to co-offend.

The process for edge prediction proposed by Zhou et al. is followed.[9] To measure the accuracy of an edge prediction algorithm on a graph G with edge set E, the set of edges is split into a training

[9] Zhou, T., Lü, L. & Zhang, YC. (2009). Predicting Missing Links via Local Information. Eur. Phys. J. B 71: 623.

set, E^T, which includes 90% of the edges and a probing set, E^P, which includes the remaining 10% of edges. The algorithm then generates a score for each edge in E^P and each edge in U/E, where U is the set of all possible edges in G. The accuracy of the algorithm is defined as the probability that an edge in E^P is given a higher score than an edge in U/E. This is measured through n independent trials. In each trial a scored edge in E^P and a scored edge in U/E are randomly selected. The accuracy of the algorithm is then given by:

$$\frac{n' + 0.5n''}{n}$$

Where n' denotes the number of times the score of the edge chosen from E^P is greater than the score of the edge chosen from U/E and n'' denotes the number of times their scores were equal.

The first scoring algorithm used is Common Neighbors (CN). The score given by CN to an edge between nodes u and v is:

$$CN(u,v) = |\Gamma(u) \bigcap \Gamma(y)|$$

$\Gamma(u)$ represents the set of neighbors of node u.

The second scoring algorithm is Adamic-Adar Index (AA). AA works similar to CN but gives more weight to shared neighbors with low degree. AA score is given by:

$$AA(u,v) = \sum_{w \in \Gamma(u) \cap \Gamma(y)} \frac{1}{\log(k(w))}$$

$k(w)$ represents the degree of w.

The last scoring algorithm is Resource Allocation (RA). RA works by modeling the amount of resource node u can send to node v through shared neighbors if each shared neighbor receives one unit of resource and then naïvely distributes it evenly to each of its neighbors.[9] The score given for an edge between u and v by RA is defined as:

$$RA(u,v) = \sum_{w \in \Gamma(u) \cap \Gamma(y)} \frac{1}{k(w)}$$

Results

As Table 4 shows, all three edge prediction algorithms performed similarly with respect to crime severity. Edge prediction proved to be more difficult for the petty co-offender network than the other two. This is for two reasons which support the findings of the assortativity analysis. First, petty crime co-offender links are harder to predict because they more often connect to an individual who has not yet engaged in criminal activity, in which case there is no local information. Furthermore, there is less trust needed between co-offenders of petty crimes because the stakes are lower. Needing less trust means an individual may choose a co-offender who less familiar and more likely to not share local information in the network. Serious crimes are easier to predict using local information because co-offenders of serious crimes are chosen with more care and often rely on a similar criminal backgrounds which manifest themselves in the network as similar node degrees. Hypothesis 3 is supported in the networks involving serious crimes as shown by the fact that RA was able to predict co-offending relationships with 85% accuracy for the network representing all crime severities. Similar to Hypotheses 1 and 2, there appears to be a separate process of selecting co-offenders for petty crimes.

Table 4 - Edge Prediction Accuracy

Alg.	All Crimes	Serious Crimes	Petty Crimes
CN	0.839	0.808	0.654
AA	0.847	0.810	0.662
RA	0.850	0.810	0.659

Conclusion

Co-offending relationships are widespread across delinquent youth.[1] Less is known, however, about the underlying processes involved in choosing with whom to co-offend. This research supports existing sociological theories in a qualitative manner. Structural and dynamical analysis of the gang shows that there are two tiers of criminality within the gang. There are also two separate processes of co-offender selection occurring within the gang, each explained by an existing theory.

Sutherland's differential association theory best explains the petty co-offender selection process. It is supported by the assortativity analysis which shows that individuals tend to commit petty crimes with people in their social circle who they learn the behavior from. Differential association is also supported by the difficulty of predicting petty co-offenders which results from a lack of local information in the graph. Differential association suggests that the relationships for serious crimes. Assortativity analysis shows that shared birthplace, a potential source of trust, and similar criminal history, a source of compromising secrets, were two of the three most predictive attributes for co-offending relationships. Furthermore, the edge prediction algorithms were more effective when applied to the serious crimes co-offender network. This shows that local information which represents criminal history is more important for predicting serious co-offending relationships.

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