Dynalink: A Framework for Dynamic Criminal Network Visualization

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Abstract—Understanding the temporal development and patterns of criminal networks is important for law enforcement and intelligence agencies to investigate and prevent crimes. Extracting and visualizing criminal networks from a large amount of crime data has been a challenge over the past years. In particular, the visualization of the dynamic development of such networks over time has been difficult in many ways. Recent advancement of visual analytics provides new analytical reasoning tools to explore and analyze a large amount of data with interactive visual interfaces. By employing the ideas of visual analytics, we propose here a framework to visualize dynamic criminal networks, which is called Dynalink. The interactive and visual features of Dynalink can be useful in discovering and analyzing both relational and temporal patterns of criminal networks.

I. INTRODUCTION

With the advancement of technology used by law enforcement and intelligence agencies, there is a critical need for new and fundamental understanding of the structure and dynamics of criminal networks. In this current paper we present a new framework to visualize dynamic criminal networks called Dynalink. Dynalink helps investigators to explore the co-offending relationships between criminals in a social network context. In order to test the functionalities of Dynalink, we have used the crime database from the Royal Canadian Mounted Police (RCMP) as test data. The case study in this paper demonstrates the usefulness of Dynalink in discovering the emergence of crime patterns according to the different crime types.

II. BACKGROUND

A social network represents a social structure which consists of actors and the dyadic ties between these actors. These ties may represent relationships, interactions, influences, and/or flows of information. By analyzing social networks, influential actors (nodes), patterns of the structure, and network dynamics can be discovered. When this idea of social networks is applied to criminal networks, co-offending networks are particular interests in investigating and preventing crime. An interactive visualization of co-offending networks would be useful as an investigative tool.

A. Social Network and Crime Pattern Analysis

Network analysis researchers study the relationships and structures of networks. By exploiting the linking structure of the network, investigators can examine the roles and behavior of nodes on a) other nodes in the network and b) the entire network. Also, observing how structures change over time can also reveal identification such as influential nodes, other local and global structures, and network dynamics.

Social network analysis (SNA) is the study of network made up by individuals or organizations. One of the fundamental assumption is the belief that causal pressures are inherent in social structure of relationships. Through the mapping of these relationships, network analysis helps to uncover the emergent and informal communication patterns present in and between individuals or organizations. The communication can be in the form of the exchange of information or goods. By mapping these relationships, emergent patterns can be observed and used to explain some of the organizational phenomena discern.

SNA has been studied for some times. Joseph Moreno was credited as introducing the formal analysis of social networks in the 1930s [1]. Originally he mapped the social network in studying the epidemic of runaways at the Hudson School for Girls in upstate New York [2]. Recently resurgence of interest in SNA are due to the advances in technology, which make large amount of data become available.

SNA extends the techniques used in network analysis and specifically in examines “the structure of social relationships in a group to uncover the informal connections between people” [3]. This includes examining the relationships, connections, or interactions of these entities. By studying e-mails, newsgroups, blogs, and other artifacts, researchers utilize social network analysis to identify communities [4]. Application of SNA often involve understanding patterns of collaboration and coordination teams for various groups, e.g. software development [5] and governance of health systems [6].

Recently, crime pattern analysis that utilizes social network information has received some attention [7] [8]. Combining the crime pattern theory that was established by the Brantinghams [9], lately SNA has become an important tool for criminologists seeking to understand the connections between patterns of interactions and criminal behaviors. The interlinking between criminal activities is used as a way to indicate relationships between communities, which can potentially identify communities of criminals. In a community, network is identified by the communication, awareness, trust,
and decision-making among its members. It was shown that SNA can produce a more effective method of detecting crime clusters.

B. Co-offending Networks

In this particular study, the criminal networks are created based on co-offending relationships among criminals. A network of co-offenders is a network of offenders who have committed crimes together [10]. With the realization of the importance of co-offending networks, law enforcement and intelligence agencies focus on criminal groups and illegal organization as well as individual suspects. Within the co-offending networks, investigators can identify those who play important roles as leaders and/or recruiters [11]. This knowledge obtained from a close inspection of co-offending networks helps law enforcement agencies establish intervention strategies [12].

There are three kinds of offenders: solo offenders, co-offenders, and offenders who commit alone and with others [10]. In general, co-offending happens more among juvenile criminals than adult criminals. Research shows that many co-offending groups and networks (particularly, juvenile ones) are unstable and such criminal relationships are short-lived. Often this is attributed to either because interventions are effective or because young co-offenders become mature so that they cease their criminal activities. Another reason can be that co-offenders become solo offenders to minimize risks as they get older.

Highly frequent offenders have a large number of different co-offenders and move among their networks to recruit individuals with whom they can commit crimes together. These recruiters usually do not choose the same person in co-offending. They also tend to select those who are younger than themselves as their co-offenders [11].

Understanding co-offending networks can reveal not only the criminal networks that were clustered but also by examining the trend and the temporal changes in the networks, we can estimate the possibility in forming of new co-offending networks in the future.

C. Visualization of Criminal Networks

Visualization of social networks is one of the important aspects of SNA. It is because visual representation of social networks aids the understanding of the network data and delivers the result of the analysis [13]. By visualizing structural information in social networks, investigators can intuitively reach certain conclusions about social networks that are not obvious with quantitative analysis [12].

There are numerous SNA tools and libraries with modules of network visualization which researchers use. For example, UCINET is a software package for the analysis of social network data [14] which comes with a visualization tool, NetDraw. Pajek [15] is another widely used software package for the analysis and visualization of large scale networks. Most of these existing software packages are limited in visualization because they have limited features in the dynamic exploration of the dataset over time. Dynamic exploration of the data will allow investigators to explore the progressive relationships between the points of interest over time. There is a need to interactive visual analytics to reveal insights in big dataset.

One of the SNA systems that visualize dynamics of criminal networks was developed by Xu et al. [16]. Their system could present the evolution process of criminal networks by employing visualization and animation methods. Later they developed another tool [17]. Based on their framework for criminal network knowledge-discovery incorporating hierarchical clustering, SNA methods, and multidimensional scaling, they developed a tool (CrimeNet Explorer) that analyzes and visualizes criminal networks using a spring embedder algorithm, which may generate nicer renderings of networks [13].

Although there have been previous attempts to visualize dynamics of criminal networks over time, the work that we present here incorporates techniques of visual analytics. Some of the techniques that require for visual analytics are visual representations and interaction techniques [18]. These techniques utilize the human eye’s broad bandwidth pathway into the mind to see, explore, and understand a large amount of data instantaneously. Actively engaging in created criminal networks through visualization and interaction have many benefits in understanding and getting insights into the networks.

III. DESCRIPTION OF THE FRAMEWORK

One of the ways of representing a network is using a graph. A graph is made up of elements called nodes and edges (often called branches) that link the nodes together [19]. Graphs are so simple that they are sometimes not as informative as other more concrete ways to represent the connections between data. However, when social networks generated from a large amount of data is to be displayed in the limited space, a simple graph representation can be good enough to show patterns of emerging social networks.

A challenging problem of displaying social networks with a large number of nodes is how to spatially organize the networks within the limited screen resolution and size. Many existing social network visualization tools provide some utilities of reorganizing the resulting networks after their automatic generation from the given data set. However, these utilities are not universally applicable. In many cases, tedious manual work is required to reorganize the networks in space for visually pleasant views even after applying such utilities. In order to overcome this problem, a network layout algorithm called spring embedder algorithm has been developed [20] [21]. The algorithm employs two principles for graph drawing: 1) Vertices connected by an edge should be drawn near each other. 2) Vertices should not be drawn too close to each other. These principles are realized through a simple physics simulation that reaches an optimal layout through a series of calculations [19]. Edges act like springs that have a target (or rest) length. Thus they try to get their lengths a little closer to their target lengths at each step. Since multiple edges can be interconnected, the nodes (elements) push and pull on one
Fig. 1. Two nodes are too close (repellence).

Fig. 2. Two nodes are too far (attraction).

Fig. 3. Initial screen of Dynalink with choices of cities.

Fig. 4. Dynalink with choices of crime types.

Fig. 5. Repositioning a node by dragging.

another until the lengths of the edges reach the equilibrium (a best-possible fit) (Figures 1 & 2). This also has an effect of self-organization for each social network that is distributed in the given space as away as possible from other networks. In other words, nodes within the same network pulling each other to make a static shape whereas nodes in different networks push each other. As a result, all the networks are evenly spread in the space.

In addition to the implementation of the spring embedder algorithm, our framework, Dynalink also uses the animation approach to visualize the changes of networks over time. Contrary to some existing social network visualization tools that simply play a slide show of still images, Dynalink animates the dynamics of organizing networks over time. Thus users can observe how a network grows and re-organizes in real time.

Dynalink also provides several visual cues that assist users to quickly perceive characteristics of social networks:

- **Node size:** As an actor gets involved with more other actors, the size of its node grows proportionally. Thus, the more co-offenders a criminal has the bigger its node becomes.
- **Node color:** A node is represented by a circle filled in with red color with different levels of brightness. When a criminal has just one co-offender, its node color is white. As he/she gets involved with more co-offenders, its color changes from bright red to dark red, and eventually black.
- **Wiggly effect:** When many nodes are interconnected with one another, they wiggle because of the forces that are applied to them. The more nodes there are the more wiggle they get. This has a visual advantage of easily finding the networks that involve many actors.

As incorporating techniques of visual analytics, particularly visual representations and interaction techniques, Dynalink provides users choices of cities and crime types (Figures 3 & 4). Dynalink enables users to interact with visual elements of networks. Users can pause the animation and investigate the networks that are created so far. Users also can interact with nodes which represent criminals. Nodes can be repositioned by dragging them to anywhere in the space (Figure 5). By clicking the middle button of a mouse on a node, the detailed information about its criminal is displayed such as crime history, gender, age, crime type, and date of crime committed (Figure 6).

As a new co-offending network is created during the animation, the detailed information about the criminal event is displayed such as crime type, detailed crime, year, month, day, hour, and minute.

Another advantage of using Dynalink is that it can process huge datasets. CrimeNet Explorer was used to analyze the sizes of the networks generated from the narcotics dataset which consisted of only 12,842 criminals [17]. Dynalink
was implemented in ProRobbery over CrimeNet Explorer.

The current version of Dynalink was implemented in Processing which is an open source programming language [22]. A reason for using Processing was that it was good for implementing an application of interactive visualization. The following case study was conducted using a laptop computer with the Intel Core i7 CPU (2.2GHz) and 12GB RAM (memory).

IV. CASE STUDY

Our framework (Dynalink) was tested against crime data provided by the Royal Canadian Mounted Police (RCMP) in British Columbia, Canada. These 5 years of real-world crime data were retrieved from the RCMP’s Police Information Retrieval System (PIRS). PIRS is a large database system that manages crime data for the jurisdictions of the Province of British Columbia, which are policed by the RCMP. The PIRS database contains information about approximately 5 million reported crime events and approximately 9 million individuals (offenders, victims, witnesses, complainants, etc.) associated with the crime events. PIRS also contains information about vehicles (about 1.4 million) and businesses (about 1.1 million) involved with crimes. From this dataset, only those offenders who were charged, chargeable, or had a charge recommended were extracted and used for the following case study. There are over 50 different crime types. For the purpose of our case study, these crime types were categorized as follow:

- **All**: this category includes all crime types.
- **Personal**: crime types that include crimes against persons (homicide, robbery, assaults, etc.).
- **Property**: crime types that include crimes against property (break and enter, theft of motor vehicle, theft over $5000, theft under $5000, etc.).
- **Robbery**: crimes such as robbery with firearms, robbery with other offensive weapon, etc.
- **Assault**: crimes such as assault-level 1, assault with weapon or causing bodily harm, aggravated assault-level 3, assault on police officer, etc.
- **Break & Enter**: break and enter-business, residence or other.
- **Theft of MV**: crimes such as theft of car over $5000, theft of truck over $5000, theft of motorcycle over $5000, etc.
- **Theft over $5000**: theft over $5000 from a motor vehicle, shoplifting or other.
- **Theft under $5000**: theft under or equal to $5000 from a motor vehicle or shoplifting.
- **Drug**: crimes such as possession of illegal drugs (cocaine, heroin, cannabis, etc.), importing and exporting illegal drugs, illegal drug trafficking, etc.

Eight major cities of the Greater Vancouver area were chosen to analyze their co-offending networks. Table I shows the approximate number of population in each city in 2006:

<table>
<thead>
<tr>
<th>City</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>203,000</td>
</tr>
<tr>
<td>B</td>
<td>400,000</td>
</tr>
<tr>
<td>C</td>
<td>115,000</td>
</tr>
<tr>
<td>D</td>
<td>45,000</td>
</tr>
<tr>
<td>E</td>
<td>94,000</td>
</tr>
<tr>
<td>F</td>
<td>69,000</td>
</tr>
<tr>
<td>G</td>
<td>81,000</td>
</tr>
<tr>
<td>H</td>
<td>35,000</td>
</tr>
</tbody>
</table>

Crime data (crime events and associated individuals) were extracted from the PIRS database for the these chosen cities and saved in the CSV (comma separated values) text format to be used by Dynalink. Dynalink created co-offending networks for each city from August 1, 2002 through July 31, 2006 and visualized them through animation over time (by date, hour, and minute) for each different crime type category.

By running Dynalink with the crime data, all the co-offending networks were generated and visualized for each crime type category. All resulting co-offending networks are interactive and can be investigated by rearranging the networks or clicking on each node to find out the details of each co-offender. Users can intuitively find patterns of the networks since they are nicely organized by themselves in space. It is easy to find similar patterns by looking at the shapes of the networks. Table II shows the numbers of co-offending networks that have eight or more than eight co-offenders for drug, property, and personal crime types in all the eight major cities. In this particular case study, large co-offending networks were of our interest. The number eight was chosen because it filtered out most of small networks. The table clearly shows that drug-related crimes tend to create large co-offending networks.

When the co-offending networks of drug-related crimes were closely investigated for each city, City B had the most number of the networks, which was fifteen. But when the numbers were normalized by calculating the rate of the number...
of co-offending networks per population, City H had the highest rate (Figure 7).

Figure 8 shows the first (forty-nine co-offenders) and third (twenty-five co-offenders) largest drug co-offending networks of all in City H. These two co-offending networks were related to marijuana production.

**Dynalink** also shows the development of co-offending networks over time through animation. Figures 9, 10, and 11 display how the co-offending networks of personal crimes had been evolved over the years in City B. Users can capture exactly when a particular network appears in the given period. Crime types of new large co-offending networks (eight or more than eight co-offenders) in Figure 9 were assault level 1 and assault on police (two large networks), assault level 1 in Figure 10 (one large networks), assault level 1 and second degree murder in Figure 11 (three large networks).

Criminal homicide is a rare event. Co-offending in homicide is even rarer. However, there had been relatively many homicides in City B, in particular, many co-offending murders. There were two large co-offending networks in committing murders: one had forty-five co-offenders, the other twelve. It is likely that these criminal events might have been gang-related activities.

**Dynalink** also visualizes the dynamic development of co-offending networks over time. It animates the emergence of new networks in the given period. This temporal visualization is important for visual analytics because the appearance of a new network at different time has a different meaning and significance. For example, Figures 9, 10, and 11 illustrate the temporal visualization of personal crime co-offending networks. The fact that both the two new large networks between August 2005 and July 2006 were related to second-degree murder signifies that period that needs a particular attention.

By applying visual analytics principles, particularly visual representations and interaction techniques, **Dynalink** can be a useful visual analytics tool for analyzing large criminal networks.

This claim was validated by conducting formal and informal

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**TABLE II**

**CO-OFFENDING NETWORKS WITH 8 OR MORE THAN 8 CO-OFFENDERS.**

<table>
<thead>
<tr>
<th></th>
<th>Drug</th>
<th>Property</th>
<th>Personal</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Cities</td>
<td>38</td>
<td>13</td>
<td>12</td>
</tr>
</tbody>
</table>

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Visual analytics is an innovative approach that combines the art of human intuition and the science of mathematical deduction to directly perceive patterns and formulate knowledge and insight from them [23]. Visual analytics tools combined with interactive visualization can be used effectively for analyzing large social networks [24]. Our framework, **Dynalink** has been developed with an emphasis on this visual analytics approach.

The presented case study demonstrates how law enforcement and intelligence agencies can use **Dynalink** to investigate co-offending networks for many different crime types. In this case study, crime data from eight major cities of British Columbia were extracted and used in **Dynalink**. By using a large amount of real-world crime data, **Dynalink** successfully processed them and generated co-offending networks. What **Dynalink** creates is an interactive visualization of co-offending networks over time. Thus, investigators can pause the animation and analyze a particular network of their interest.

After generating all co-offending networks, it was easy to find patterns of these criminal networks because they had well-organized shapes with different node sizes and colors as well as wiggly effect. It was discovered that drug-related crime types had most of large co-offending networks. It was apparent to see how different cities have different patterns of criminal networks. This provides law enforcement and intelligence agencies an insight to devise strategic plans for intervention or preventing crimes.

**Dynalink** also visualizes the dynamic development of co-offending networks over time. It animates the emergence of new networks in the given period. This temporal visualization is important for visual analytics because the appearance of a new network at different time has a different meaning and significance. For example, Figures 9, 10, and 11 illustrate the temporal visualization of personal crime co-offending networks. The fact that both the two new large networks between August 2005 and July 2006 were related to second-degree murder signifies that period that needs a particular attention.

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Figure 7. Number of drug co-offending networks per population.

Figure 8. Drug co-offending networks in City H.

Figure 12. Co-offending networks for homicide in City B.

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Fig. 9. Personal crime co-offending networks in City B until July 2004.

Fig. 10. Personal crime co-offending networks in City B until July 2005.

Fig. 11. Personal crime co-offending networks in City B until July 2006.
expert reviews. A few crime analysts and crime analysis researchers tried out Dynalink and mostly provided positive feedback. Dynalink was also reviewed by a current police officer who had fourteen years of police service (particularly, four years of investigating networks of criminals). She pointed out the usefulness of visualizing the temporal progression in forming networks, which enables a temporal analysis. She also recognized the ease of finding patterns of criminal networks with network shapes, node sizes and colors, and wiggly effects. She suggested that Dynalink could be improved by visualizing any possible connections between different networks.

VI. CONCLUSION AND FURTHER RESEARCH

Visualizing social/criminal networks often emphasizes on the relational aspect only, overlooking the temporal aspect. One reason for this is the difficulty of automatically organizing networks nicely in the given space in real time. However, by disregarding the temporal aspect of social/criminal networks, sometimes crucial knowledge and insights can be missed in analyzing the networks. Another lacking feature of many existing social network visualization tools is interaction. Visual analytics principles include visual representations and interactions techniques, so that investigators can interact with such visual representations and intuitively perceive emerging patterns of the networks. Our proposed framework, Dynalink tries to include such features: visualizing the temporal aspect of social/criminal networks with animation and enabling interactions with all the nodes of the networks. By applying the spring embedder algorithm, Dynalink organizes the networks nicely in the given space. Many visual cues such as node size, color, and wiggly effects help investigators easily detect specific networks that need an attention. Our case study demonstrates some practical uses of Dynalink in analyzing co-offending networks. The interactive and temporal visualization of criminal networks is an enabling factor for analytical reasoning in any criminal investigations by law enforcement and intelligence agencies.

Our current framework has limited features with its focus on visualization and interaction. It also has a limitation of animating and visualizing only criminal networks. Future work can include adding simple statistics such as calculating the number of networks with the different number of nodes, a graph showing the growth of networks over time, and comparison charts and/or graphs among the networks of different categories. The graphical user interface (GUI) can be improved with a better looking and modernized controls. The framework can be extended to visualize other kinds of networks such as terrorists’ networks and networks of harmful websites. Visualizing geolocations of nodes is also possible if these information are available. In addition, augmenting the current system to include three dimension visualization with hand-gesture interaction and a big display might be challenging but possible with current technologies. While adding these new features, more extensive usability evaluation will be conducted.

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