Learning, Predicting and Planning against Crime: Demonstration Based on Real Urban Crime Data

(Demonstration)

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Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence - multiagent systems

1. INTRODUCTION

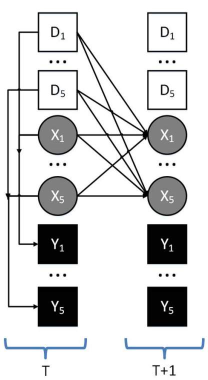

Figure 1: DBN

Crime in urban areas plagues every city in all countries. This demonstration will show a novel approach for learning and predicting crime patterns and planning against such crimes using real urban crime data. A notable characteristic of urban crime, distinct from organized terrorist attacks, is that most urban crimes are opportunistic in nature, i.e., criminals do not plan their attacks in detail, rather they seek opportunities for committing crime and are agile in their execution of the crime [1, 2]. Police officers conduct patrols with the aim of preventing crime. However, criminals can adapt their strategy in response of police deployment by seeking crime opportunity in less effectively patrolled location. The problem of where and how much to patrol is therefore important.

In this presentation we propose a novel approach to learn and update the criminal behavior from real data [3]. We model the interaction between criminals and patrol officers as a Dynamic Bayesian Network (DBN). Figure 1 shows an example of such DBN. Next, we apply a dynamic programming algorithm to generate optimal patrol strategy against the learned criminal model. By iteratively updating the criminals' model and computing patrol strategy against them, we help patrol officers keep up with criminals' adaptive behavior and execute effective patrols. This process is shown as a flow chart in Figure 2.

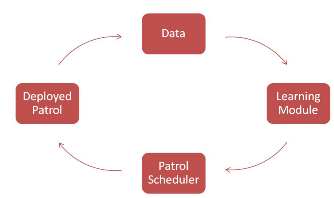

Figure 2: Scheduler flowchart

With this context, the demonstration presented in this paper introduces a web-based software with two contributions. First, our system collects and analyzes crime reports and resources (security camera, emergency supplies, etc.) data, presenting them in various forms. Second, our patrol scheduler incorporates the algorithm in [3] in a scheduling recommendation system. The demonstration will engage audience members by having them participate as patrol officers and using the software to 'patrol' the University of Southern California (USC) campus in USA.

2. MULTI-USER SOFTWARE

Our multi-user web-based software is built for the Department of Public Safety in University of Southern California. It is composed of two main components: a data collector and a patrol scheduler. A detailed demonstration of our software can be found here.

2.1 Data collector

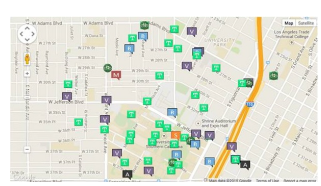

Figure 3: Crime analysis

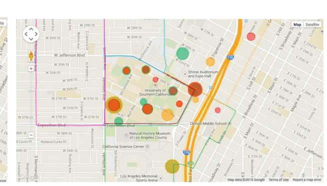

Figure 4: Hotspot analysis

The data collector receives crime data from police department, and presents and analyzes it in various fashions. There are three main tasks of the data collector: First, it visualizes crime data with spatial and temporal information,

Appears in: *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May 4–8, 2015, Istanbul, Turkey.*

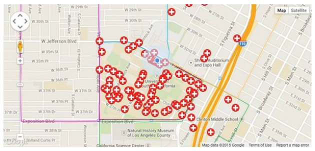

Figure 5: Emergency supply

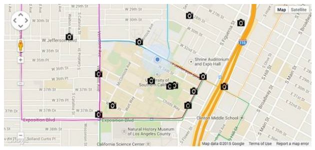

Figure 6: Security Cameras

as shown in Figure 3, to help officers analyze the trend of crimes around campus. As shown in Figure 4, 'hot' areas indicates attractive targets for criminals to commit crimes. Police department can cool down these hot spots by increasing patrol coverage when assigning officers in the field.

Second, the data collector provides information to the officers in the field about various available resources such as emergency supplies and security cameras. As shown in Figure 5, our software indicates the location for all the emergency supplies on campus. Figure 6 shows the (mock) location of security cameras. To check certain locations, officers can use our software to watch the video from any camera.

Finally, the data collector provides input for the patrol scheduler. By reading the data from collector, patrol scheduler can continuously learn and update criminals' behavior.

2.2 Patrol scheduler

2.2.1 *Patrol settings*

In USC, our approach divides the enforcement area (encompassing the campus) into 18 patrol areas, which is shown in Fig 7. DPS patrols would be in shifts of 4 hours each. At the beginning of each patrol shift, our algorithm assigns each available patrol officer to a patrol area and the officer patrols this area in this shift. At the same time, the criminal is seeking for crime opportunities by deciding which target they want to visit. Discussions with DPS reveals that criminals act opportunistically, i.e., crime is not planned in detail, but occurs when opportunity arise and there is insufficient presence of DPS officers.

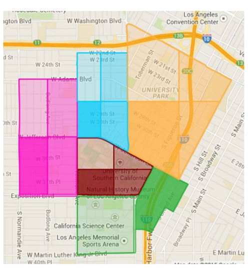

Figure 7: Patrol area

2.2.2 *Schedule generator*

To generate patrol schedule for DPS officers, we apply the algorithm introduced by [3]. As a brief introduction to the algorithm, the DBN model captures the following actions: in each time step the defender assigns officers to protect all patrol areas and criminals react to the defenders' allocation strategy by committing crimes opportunistically. Across time-steps the criminals respond to police patrols by moving from a target to another. Using real data, we learn the criminal behavior as modeled in the DBN. We represent the DBN compactly, leading to improved performance. Finally, dynamic programming based method is used to find the optimal defender plan for learned model. We highlight the recommended patrol area on campus map, as shown in Figure 8.

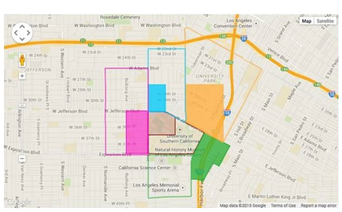

Figure 8: Sample patrol schedule

3. DEMONSTRATION INTERACTION

In our demonstration, the audience members will be able to directly interact with our software in three ways: first, the audience can use data collector to analyse crime and request assistance as an officer. As stated in Section 2.1, the audience can set up constraints to view certain crimes and hotspots. Also, they can check the details of a crime by clicking on icons. Also, audience can check emergency supplies and video stream from security cameras (pre-recorded video will be used due to sensitive nature of real time video).

Second, the audience can change weights of the different crime types and the number of resources in the patrol scheduler to change the recommended patrols. Finally, the audience can evaluate the patrol scheduler in our software by creating artificial incidents. Given the crime and patrol history, the audience can act as criminals and pick targets to attack. Our patrol scheduler will learn the audiences' behavior from their choice, predicting their next move and generating optimal patrol strategy against them. The audience can evaluate our software by comparing their crime decision with our prediction.

4. ACKNOWLEDGEMENT

This research is supported by MURI grant W911NF-11-1-0332.

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