ABSTRACT

Police patrols are used ubiquitously to deter crimes in urban areas. A distinctive feature of urban crime is that criminals react opportunistically to patrol officers' assignments. Compared to strategic attackers (such as terrorists) with a well-laid out plan, opportunistic criminals are less strategic in planning attacks and more flexible in executing them. I proposed two approaches to generate effective patrol schedules against opportunistic criminals. The first approach is a new game-theoretic framework for addressing opportunistic crime, the Opportunistic Security Game(OSG). In OSG, I propose a novel model for opportunistic adversaries. The second approach is to learn the criminals' behavior model from real-world criminal activity data. To that end, I represent the current behavior and the interaction with the patrol officers as parameters of a Dynamic Bayesian Network (DBN), enabling application of standard algorithms such as EM to learn the parameters. Finally, I show that a sequence of modifications of the DBN representation in learning approach, which exploit the problem structure in model approach, result in better accuracy and increased speed. By combining modeling and learning approaches, I can generate patrol schedule which has significantly better performance.

Keywords

Game theory; Security games; Optimization

1. INTRODUCTION

Crime in urban areas plagues every city in all countries. 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 [3, 5]. In order to deter such crimes, police officers conduct patrols with the aim of preventing crime. However, by observing on the spot the actual presence of patrol units, the criminals can adapt their strategy by seeking crime opportunity in less effectively patrolled location. The problem of where and how much to patrol is therefore important.

There are two approaches to solve this problem. The first approach is to determine patrol schedules manually by human planners, which is followed in various police departments. However, it has been demonstrated that manual planning of patrols is not only time-consuming but it is also highly ineffective in many related scenarios of protecting airport terminals [2]. The second approach is to use automated planners to plan patrols. Stackelberg Security Game (SSG) has become an important computational framework for allocating security resources in such planners. However, SSG was proposed to model highly strategic adversaries who conduct careful surveillance and plan attacks [4]. While there are such highly capable adversaries in the urban security domain, they likely comprise only a small portion of the overall set of adversaries. Instead, the majority of adversaries are criminals who conduct little planning or surveillance before “attacking” [1].

I proposed the Opportunistic Security Game (OSG), a new computational framework for generating defender strategies to mitigate opportunistic criminals [5], where I considered the criminal’s opportunistic behavior such as Quantal Biased Random Movement, a stochastic movement to search for crime opportunities, and reaction to real-time information. However, the proposed game-theoretic model of criminal behavior has not been validated with real data.

Hence, in [6], I shed a new light into this problem, by presenting a novel approach to learn the criminal behavior from real data. By modeling the interaction between the criminal and patrol officer as a Dynamic Bayesian Network (DBN), we can predict criminals’ reaction to defender’s strategy and design the optimal patrol strategy correspondingly.

Moreover, I also combined these two approaches, performing simplifications of the DBN representations that exploit the interaction between defenders and opportunistic criminals in OSG. These simplifications result in a compact DBN representation. In the compact DBN, I achieve better accuracy and increased speed of the EM algorithm.

2. PATROL SCHEDULER

I briefly summarized the three patrol schedulers developed. The first is the game-theoretic framework, Opportunistic Security Games. The second approach is Dynamic Bayesian Network for learning and finally the combination of two approaches, the compact Dynamic Bayesian Network.

2.1 Opportunistic Security Game

The Opportunistic Security Game unfolds on a connected
Our model of the criminal consists three components. First is criminal’s probability to commit a crime at current target at current time step. This probability depends not only on the defender’s coverage of this target, but also on the attractiveness of this target. Attractiveness measures how likely a criminal located at that target is to commit a crime in the absence of defenders. The second is criminal’s belief state of defender. At each time step, the criminal uses his knowledge of defender’s strategy and his real-time observation to update his belief of defender. Given such belief state, he may calculate the expected utility for each target. The final component is criminal’s Quantal Biased Random Movement(QBRM). QBRM models the criminal’s bounded rationality based on other such models of criminal movements in urban domains. Instead of always picking the target with highest expected utility, his movement is modeled as a random walk biased toward target of high expected utility.

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Finally, these algorithms will eventually be implemented in real urban area for evaluating and improving. I will implement these algorithms to schedule patrol strategies on campus with the help of the Department of Public Safety in University of Southern California. To fill the gap between simulation and implementation, I need to consider practical constraints such as the appearance of events, e.g., football games, and emergency. Meanwhile, the defender’s patrol preference is also an important factor. For example, within the same target area, some officers spend more time near library while others patrol gym more frequently. Also, building a potable device or software for the officers is a non-trivial task. I have submitted the initial model to the Demo session of AAMAS 2015 and I will keep improving it.

REFERENCES