Modeling, Learning and Defending against Opportunistic Criminals in Urban Areas

(Doctoral Consortium)

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ABSTRACT

Police patrols are used ubiquitously to deter crimes in urban areas. A distinctive feature of urban crimes 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 criminal 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.

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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 graph that can be seen to model an urban area, where potential targets are nodes and paths connecting two targets are edges. A defender is a team of police officers conducting randomized patrol in this area to mitigate crime.

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.

I computes the optimal defender strategy by modeling the OSG as a finite state Markov chain. Each state of this Markov chain is a combination of the criminal's and defender's location. Given this Markov chain model, the expected number of crime at each step can be calculated since I know the location of both players. The objective of defender is to minimize the total number of crimes over all the steps. Thus I have formulated the defender's problem of finding a optimal patrol strategy as a optimization problem, specifically to minimize the total number of crimes.

2.2 Dynamic Bayesian Network

Dynamic Bayesian Network(DBN) is proposed to learn the criminals' behavior, i.e. how the criminals pick targets and how likely are they to commit crime at that target. In every time-step of the DBN I capture the following actions: the defender assigns patrol officers to protect N patrol areas and criminals react to the defenders' allocation strategy by committing crimes opportunistically. Across time-steps the criminal can move from any target to any other, since a time-step is long enough to allow such a move. The criminals' payoff is influenced by the attractiveness of targets and the number of officers that are present. These payoffs drive the behavior of the criminals. However, rather than model the payoffs and potential bounded rationality of the criminals, we directly learn the criminal behavior as modeled in the DBN. I can apply the EM algorithm to learn the unknown parameters in DBN.

2.3 Compact Dynamic Bayesian Network

I use three modifications to make DBN model compact. (1) I infer from the available crime data that crimes are local, i.e., crime at a particular target depends only on the criminals present at that target. Using this inference, I constructed a factored output matrix that ignores non-local crimes. (2) Next, I rely on intuition from the Boyen-Koller(BK) algorithm to decompose the joint distribution of criminals into a product of independent distributions for each target. (3) I conclude that opportunistic criminals by and large work independently. Using this independence of behavior of each criminal, I reduce the size of the transition matrix in DBN. Applying the EM algorithm to the compact DBN model, I can learn the criminal's behavior.

3. NEXT STEPS

Many research directions are still open, and I will keep developing further. I plan to defend my thesis in May 2016, so there is still a significant amount of research to be developed.

First, the runtime of current algorithm grows exponentially to the scale of the problem and the number of officers. A nature question is whether there is a fast algorithm for recommending patrol strategies. After doing a survey on existing literature, I haven't found an fast approach for my model. Therefore, I am working on a fast algorithm for generating patrol strategy. Moving forward, I also expect to generate patrol schedule in a detail level. Current approaches consider the urban area in an abstract level, ignoring the internal structure for each target. In reality, such internal structure, such as the platform and parking lots of a train station and the library on campus, is crucial for designing patrol. Therefore, more sophisticated approaches are needed for these situations.

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.

4. ACKNOWLEDGEMENT

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