Green Security Game with Community Engagement

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Abstract

Green security problems such as protecting wildlife from poaching and protecting fisheries from illegal fishing are particularly challenging due to the frequent illegal activities and a very low average density of defensive resources, i.e., patrollers. To assist the patrols, community members sometimes provide informative tips that can lead the patrollers to areas with high probability of having illegal activities.

While game theoretic models and algorithms have been developed to handle challenges in green security domains, none of these models consider such community engagement. In this paper, we introduce a novel two-stage green security game model that takes into account community engagement and provide initial complexity results, a poly-time algorithm for special cases as well as results of a case study on the tradeoff between hiring patrollers and informants.

1 Introduction

Security problems exist all around the world in various domains, with the shared challenge that sufficient security coverage is not always possible due to the lack of defensive resources. Game-theoretic models have been proposed to model the defender-attacker interaction [Tambe, 2011] and exact and approximate algorithms have been developed to compute an efficient allocation of defensive resources [Kiekintveld *et al.*, 2009; Conitzer and Sandholm, 2006]. These game models and algorithms tackle problems in infrastructure security domains such as protecting airports and public transportation from terrorists [Pita *et al.*, 2008; Jain *et al.*, 2010; Yin *et al.*, 2012; Fang *et al.*, 2013], green security domain such as protecting wildlife, fishery, and forest from poaching [Yang *et al.*, 2014; Fang *et al.*, 2015], illegal fishing [Haskell *et al.*, 2014; Qian *et al.*, 2014] and illegal logging [McCarthy *et al.*, 2016].

In green security domains, a common lack of funding leads to a extremely low density in defensive resources. For example, it is reported in a wildlife crime study [Holmern *et al.*, 2007] that an actual coverage density is 1 patroller per 167 square kilometers. Furthermore, illegal activities are conducted repeatedly and frequently in these domains, making it even harder for the law enforcement agencies (referred to as defenders) to provide effective protection. Due to the harshness of the situation, the defenders often rely on local community to thwart the criminal activities. For example, the defender will plan patrols based on tips provided by his informants, which contain detailed information about recently conducted or upcoming criminal activities. This is a common practice in wildlife conservation. In fact, community engagement is listed by World Wild Fund for Nature as one of the six pillars towards zero poaching, parallel to ranger patrols [WWF, 2015b; WWF, 2015a]

In criminology, community engagement is being studied in anti-poaching [Moreto, 2015] and reducing crime [Tublitz and Lawrence, ; Maguire and John, 2006; Gill *et al.*, 2014]. [Moreto, 2015] provides an investigation of community-ranger relations from the view point of rangers from a wildlife organization in Uganda. However, to our knowledge, there is no computational model or game theoretic model for green security problems that takes community engagement into account.

In this paper, we present (i) an initial two-stage green security game model with community engagement; (ii) complexity results for solving the game and a poly-time algorithm for solving the case where the number of informants we can hire is a constant; (iii) results of a case study on the tradeoff between the numbers of hired informants and patrollers; (iv) challenges and future directions. In our model, we consider a social network among a group of people (e.g. villagers who live around a conservation area). Defenders are given a certain amount of defensive resources and are able to hire informants. Our goal is to find the optimal strategy of hiring informants in terms of maximizing defenders' utility. We show that this optimization problem is NP-Hard even in a simple case.

2 Related Work

In criminology, [Smith and Humphreys, 2015; Moreto, 2015; Duffy *et al.*, 2015] investigates the relationship between rangers and comminuty members and explore the role that community engagement plays in wildlife conservation. For fighting urban crime, [Tublitz and Lawrence,] shows that a program that focuses on improving the relationship between the police and residents help reducing crime in two urban areas. [Maguire and John, 2006] studies the role of an intelligence model that incorporates the perspectives of partner agencies and local communities with parameters for both reactive and proactive responses to crime. [Gill *et al.*, 2014] shows that community-oriented policing strategies help improve perceptions of the police and has positive effects on police legitimacy. As for fighting terrorism, [Briggs, 2010] outlines a case for a community-based approach in the UK including key developments since 2005 and [Spalek and Imtoual, 2007] suggests a more socially inclusive approach should be applied so that working with a boarder range of communities would be encouraged. However, these work do not study community engagement from the lens of computational game theory.

Recruitments of informants have also been proposed to study societal attitudes in relation to committing and reporting crime using evolutionary game theory models. [Short *et al.*, 2010] shows that the presence of informants can lead to decrease in crime and [Short *et al.*, 2013] formulates the problem of solving recruitment strategies as an optimal control problem account for limit resources and budget. In contrast to their work which focuses on crime reporting only, we emphasize on the synergy of community engagement and allocation of defensive resources, and aim to find the best strategy of recruiting informants and allocating patrollers.

3 Motivating Domains

An example motivating domain of our work is anti-poaching. Conservation agencies send rangers to patrol in a conservation areas to protect wildlife from poachers. The actions of the poachers sometimes can be perceived by villagers who are living around the conservation areas. For example, a poacher may talk about his poaching plan when he eats in a restaurant or goes karaoke singing with his friends. Such information, if known to the patrollers, can directly be used to guide the patrols. Therefore, the conservation agencies will recruit informants from the villagers and pay them if they provide useful information (often called tips). Based on the defender's understanding about the social work, they often reach out to people who has most access to poachers, e.g., waiters at restaurants. However, it remains a research challenge how they should recruit informants and how they should plan patrols optimally with or without tips provided by the informants. Similar challenges with community engagement exist in fighting opportunistic crime, infrastructure protection, forest and fishery protection.

4 Methodology

In this section, we introduce a new two-stage green security game model with community engagement. The game we consider in this paper features a set of n targets $T = [n]$ and two sets of villagers X and Y where X are potential informants, Y are potential poachers and $X \cap Y = \emptyset$.

The defender has r unit of defensive resources, each can protect one target. The defender's payoff for a covered attack on target i is denoted $R_i^d > 0$ and for an uncovered attack $P_i^d < 0$. Similarly, $P_i^a < 0$ and $R_i^a > 0$ are the attacker's payoff.

Those potential informants X, are people who will not conduct poaching activities, while the potential poachers Y are those who will go poaching with some probability. Formally, for each $v \in Y$, we assume that v attacks a target with probability p_v but the target is unknown and each of them takes action independently. Let $G_S = (X, Y, E)$ be a bipartite graph that represents the social network, where an edge $(u, v) \in E$ with an information sharing intensity w_{uv} represents that if $u \in X$ is hired as an informant, u will report the targeted location of $v \in Y$ with probability w_{uv} given v go poaching. We say that a target is *reported* if the target is reported by an informant that it is poaching location by an attacker, otherwise it is *unreported.* Say that the defender is *informed* when getting at least one targeted location from U.

In the first stage of the game, the defender hires k informants, then in the second stage, r unit of defensive resources are allocated. The defender's goal is to hire a set of k informants in the first stage in order to maximize the expected utility in the second stage.

While in the second stage, we adopt the concept of Strong Stackelberg Equilibrium (SSE) [Kiekintveld *et al.*, 2009]. For the defender, she will follow a SSE strategy when she get no tip from the informants and the attackers can observe the strategy. Let Γ be the set of attackers' best responses to the observed strategy, breaking tie in favour of the defender. For each of the attackers, since they are not aware of informants, we assume that they will always follow the mix strategy that uniformly mixes the pure strategy in Γ. When the defender is informed, she will be tip-driven and adopt the optimal strategy that first allocates the defensive resources to whichever targets there will be an attacker for sure and allocates the rest to other targets. That is, if there are more than r targets reported, the defender will choose r targets among those to maximize her utility, otherwise she will cover all the reported targets, and optimally allocate the rest of the resources unreported targets.

4.1 Complexity Results

By the following theorem, we show the NP-Hardness for solving the optimization problem.

Theorem 1. *Computing the optimal set of informants to hire is NP-Hard even with $r = 1$ and uniform targets (R_i^d's (R_i^a, P_i^d, P_i^a) are the same for all i).*

Proof. Let $U \subseteq X$ where $|U| \leq k$ be the set of informants we hire and $V = \{v : (u, v) \in E \wedge u \in U\}$. Denote P as the probability of being informed. Since the targets are uniform, the SSE for the defender (attacker) is to allocate the resource (launch attack) at each location with probablity $\frac{1}{n}$. Let random variables X_i be the number of attacked targets among $T \setminus \{i\}$ and $Y_i \in \{0, 1\}$ indicates whether i is attacked given i is covered (1 for attacked). Let U_0 and U_1 be the expected utility given being informed and not being informed respectively. Hence we have

$$U_0 = E[X_1 | Y_1 = 1] P^d + R^d$$

and

$$
\begin{aligned}
U_1 &= \sum_{i\in[n],j\in\{0,1\}} \frac{1}{n}\Pr[Y_i=j](E[X_i|Y_i=j]P_d + j\cdot R_d) \\
&= \sum_{j\in\{0,1\}} \Pr[Y_1=j](E[X_1|Y_1=j]P_d + j\cdot R_d),
\end{aligned}
$$

where $R^d = R_i^d$ and $P^d = P_i^d$ for all i. Thus the expected utility could be written as

$$\mathsf{DefEU} = PU_0 + (1-P)U_1.$$

Since $E[X_1|Y_1=1] < E[X_1|Y_1=0]$, we have $U_0 > U_1$. Thus solving for the optimal solution of the original problem is equivalent to solving for U that maximizes P in the first stage.

We use a reduction from maximum coverage problem (MCP) to show that the optimization problem is NP-Hard.

Consider an instance of MCP where a number k and a collection of sets S, the objective is to find a subset $S' \subseteq S$ of sets such that $|S'| \le k$ and the number of covered elements $\left|\bigcup_{S_i\in S'} S_i\right|$ is maximized.

Let $X = \{x_1,\ldots,x_{|S|}\}$, $Y = \bigcup_{S_i\in S} S_i$, $E = \{(x_i,y) : i \in [|S|] \wedge y \in S_i\}$, $p_v = 0.5$ for all $v \in Y$ and $W_e = 1$ for all $e \in E$. Thus $P = 1 - \prod_{v\in V}(1-p_v) = 1 - 0.5^{|V|}$. To maximize the objective value is to find a U with $|U| \le k$ that maximize the size of V, which in the instance of MCP, is equivalent to finding a subset of sets with size no larger than k that maximizes the number of covered elements. □

4.2 A Poly-Time Algorithm for Constant k

Algorithm 1 Calculate $\mathsf{DefEU}(U,\Gamma)$

for $v \in V$ **do**
  $t_v \leftarrow p_v\left(1 - \prod_{(u,v)\in E, u\in U}(1-w_{uv})\right)$
Expand the polynomial $\prod_{i\in V}(t_i x + 1 - t_i) = \sum_{i=0}^{|V|} f_i x^i$
$r \leftarrow \min(r, |\Gamma|)$
for $0 \le j \le |\Gamma|$ **do**
  $q_j \leftarrow \sum_{i=j}^{|V|} f_i \left\{{i \atop j}\right\}\binom{|\Gamma|}{j} j!/|\Gamma|^i$
$g \leftarrow 1 - \prod_{v\in V}(1 - t_v/|\Gamma|)$
$h \leftarrow 1 - \prod_{v\in Y}(1 - p_v/|\Gamma|)$
$S \leftarrow 0$
for each target $c_i \in \Gamma$ **do**
  if $i \le r$ **then**
    $a_i \leftarrow \sum_{j=0}^{|\Gamma|}\sum_{k=0}^{\min(j,r-i)} q_j \binom{|\Gamma|-i}{k}\binom{i-1}{j-k}/\binom{|\Gamma|}{j}$
    $S \leftarrow S + g\cdot R_i^d + (h-g)(a_i/(1-g)R_i^d + (1 - a_i/(1-g))P_i^d)$
  else
    $a_i \leftarrow \sum_{j=0}^{|\Gamma|}\sum_{k=0}^{\min(j,r-1)} q_j \binom{i-1}{k}\binom{|\Gamma|-i}{j-k-1}/\binom{|\Gamma|}{j}$
    $S \leftarrow S + a_i R_i^d + (h-a_i)P_i^d$
return S

We show that given k is a constant, the optimal recruitment strategy and the optimal defenders' utility can be computed in polynomial time. To show that, we start by proving the following lemma.

Algorithm 2 Main Algorithm

Input G_S, n, k and the defender's and attackers' payoff
Compute Γ
$\mathsf{OPT} \leftarrow \emptyset$
for $U \subseteq X$, $|U| \le k$ **do**
  $S \leftarrow \mathsf{DefEU}(U,\Gamma)$
  Update OPT with (U,S)
return OPT

Lemma 1. *Given the set of hired informant, the defender's expected utiliy can be computed in polynomial time.*

Proof. To prove the lemma, we show a polynomial time algorithm for computing the optimal utility.

The calculation is based on the observation that targets in Γ are indifference to attackers and given the tips from informant, the optimal allocation of r resources to reported(unreported) targets is to greedily allocate resources to r targets with highest $R_i^d - P_i^d$.

First, we define the notation used in the algorithm. Let U be the set of hired informants, $V = \{v : (u,v) \in E \wedge u \in U\}$, t_i be the probability of the poaching location of poacher i is reported by U, f_i be the probability of knowing exactly i poachers' location. Since targets in Γ are indifference to attackers, we can define g, h be the probability of a given target is reported and is attacked, and q_j be the probability of exactly j targets are reported. Let $\Gamma = \{c_1,\ldots,c_{|\Gamma|}\}$ and suppose $R_{c_i}^d - P_{c_i}^d \ge R_{c_j}^d - P_{c_j}^d$ for all $i > j$. For $i \le r$, let a_i be the probability of target c_i being covered but not being reported and for $i > r$, let a_i be the probability of target c_i being covered and reported. $\binom{n}{k}$ and $\left\{{n \atop k}\right\}$ denote the binomial coefficient and Stirling number of the second kind.

Algorithm 1 shows the computation of the defender's utility could be done in $O(|Y|^2 + n^3)$ time, which concludes the proof.

□

Theorem 2. *Given k is a constant, the optimal recruitment strategy and the optimal defenders' utility can be computed in polynomial time.*

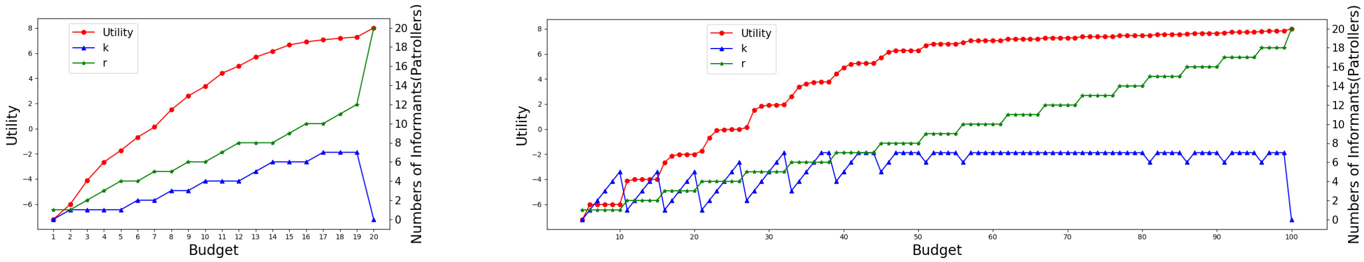
Proof. All possible recruitment strategies can be enumerate in $O(|X|^k)$ and Γ can be computed in polynomial time as shown in [Kiekintveld *et al.*, 2009]. Algorithm 2 shows the computation of the optimal solution. By Lemma 1 and since k is a constant, it is a poly-time algorithm.

□

4.3 The Tradeoff Between the Numbers of Hired Informants and Patrollers

In this part, we study the tradeoff between the numbers of hired informants and patrollers. We are given a budget B, where informants and patrollers can be hired at a cost C_i and C_p each.

Solving for the optimal k informants and r patrollers to hired is NP-Hard, since by enumerating all possible k and r such that $k\cdot C_i + r\cdot C_p \le B$, the subproblem of computing



(a) $C_i = 1, C_p = 1$

(b) $C_i = 1, C_p = 5$

Figure 1

the optimal set of informants to hire is NP-Hard as shown previously.

To show the tradeoff between k and r, we focus on simple cases with uniform targets and plot graphs that show how the optimal number of informants and number of patrollers change as the budget increases on a sample case.

In the sample case, there are $n = 20$ uniform targets with $R^d = 1$ and $P^d = -1$. We have the social network among 20 informants and 20 potential poachers. The bipartite graph $G_S = (X, Y, E)$ that represents the social network is generated randomly, where for each informant $u \in X$ the degree is drawn uniformly from 1 to 6 and the set of out-going edges from u is also drawn uniformly. For all $v \in Y$, p_v is drawn from $U[0, 1]$ and for all $e \in E$, $w_e = 1$.

We show the optimal defenders' utility and the optimal recruitment strategies for different budget on two cases. In the first case, we let $C_i = C_p = 1$ and the result is shown in Figure 1(a). In the second case $C_p = 5, C_i = 1$ and the result is shown in Figure 1(b).

5 Challenges and Future Directions

In this paper, we introduced a two-stage green security game model that incorporates community engagement, showed the NP-Hardness of solving the optimal strategy of hiring informants and a poly-time algorithm for solving the case for constant k, presented results of a case study on the tradeoff between the numbers of hired informants and patrollers.

For future work, there are several challenges and directions that we can potentially pursuit. First, we can model the attackers having different types, such as having different preferences on targets. Second, different behavioral models can be applied to the attackers. For example, the attackers may respond to the observed marginal strategy instead of SSE strategy. Assuming bounded rationality on attackers would also be reasonable in reality. Third, different types of ranger presence can be considered in the models. Besides sending rangers to the forest for regular patrol, rangers can also be dispatched in uniform to villages, where poachers show up frequently in particular, to show deterrent to crime based on reliable tips from informants. Therefore, we can model presence in and outside conservation area and study the tradeoff between types of presence.

Furthermore, we can model the informants as strategic agents. In real life, it is possible to have a more complicated situation where informants may also commit crime and be not willing to cooperate with authorities. For example, they may cover criminal activity for their own interest, and sometimes frame a case against someone they do not like, or disrupt rangers' work if they dont like the rangers. For paying informants, conservation agencies should not pay too much so people will not take it as a way for easy money, while also not too less to have people stay with you. The problem can be formulated as a mechanism design problem, where we want to design a mechanism for hiring and paying both informants and patrollers to elicit true information as well as maximizing defenders' utility.

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