When Security Games Go Green

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Outline

Green Security Game

□ Planning algorithms

□ Planning and learning

□ Results

Green Security Domains: Protecting Fish and Wildlife





Features

Green security games

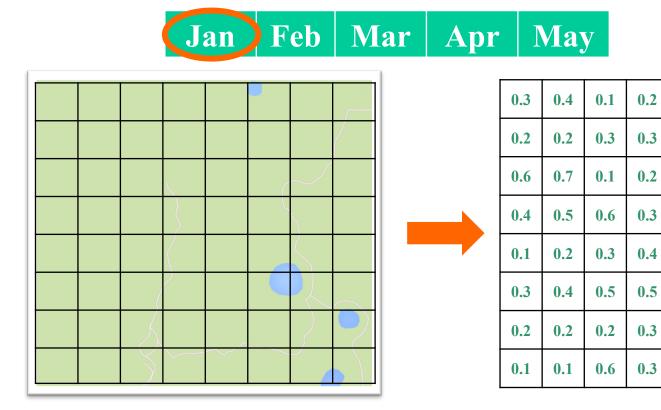
- Generalized Stackelberg assumption
- **D** Repeated and frequent attacks
 - Significant amounts data
- □ Attacker bounded rationality
 - Limited surveillance/planning

Green Security Game Model

 \Box *T* round game, K defenders, N targets where N \geq *K*

\Box Coverage vector $c = \langle c_i \rangle$ where

- c_i denotes probability that target i is covered
- c^t denotes the defender strategy profile for round t



0.5

0.4

0.3

0.1

0.5

0.5

0.3

0.4

0.1

0.6

0

0.3

0.4

0.1

0.4

0.4

0

0.5

0.2

0.2

0.3

0.1

0.3

0.2

0.7

0.1

0.9

0

0.1

0.1

0.5

0.4

Green Security Game Model

- L attackers who respond to convex combination of defender strategy in recent rounds
 - $\Box \eta^t$ denotes the strategy of attacker for round t

JanFebMarAprMay
$$c^1$$
 c^2 $c^3=?$

$$\eta^3 = 0.3c^1 + 0.7c^2$$

- \Box Payoff values for target i P_i^a , R_i^a , P_i^d , R_i^d
 - □ Where P stands for Penalty, R for reward
 - \square a for attacker, d for defender
- □ Expected utility for defender d if attacker targets i □ $U_i^d(c) = c_i R_i^d + (1 - c_i) P_i^d$

Green Security Game Model

- □ Attacker chooses target with bounded rationality
 - □ Following the SUQR model
 - Choose <u>more promising targets</u> with higher probability
 Probability that an attacker attacks target i is

$$\Box q_i(\omega,\eta) = \frac{e^{\omega_1 \eta_i + \omega_2 R_i^a + \omega_3 P_i^a}}{\sum_j e^{\omega_1 \eta_i + \omega_2 R_i^a + \omega_3 P_i^a}}$$

- \Box Create a defender strategy profile $[c] = \langle c^1, ..., c^T \rangle$
- □ Expected utility of defender in round t

$$\Box E^{t}([c]) = \sum_{l} \sum_{i} q_{i}(\omega^{l}, \eta^{t}) U_{i}^{d}(c^{t})$$

Outline

Green Security Game Model

□ <u>Planning algorithms</u>

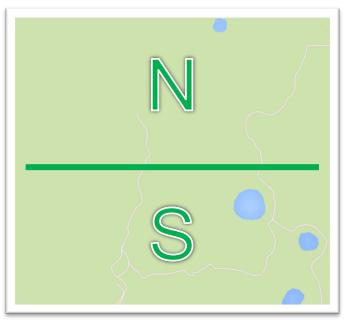
Planning and Learning

□ Results

Planning

 \Box Exploit attackers' delayed observation ($\eta^t = c^{t-1}$)

- \Box A simple example:
 - Patrol Plan A: always uniformly random
 - Patrol Plan B: change her strategy deliberately, detect more snares overall



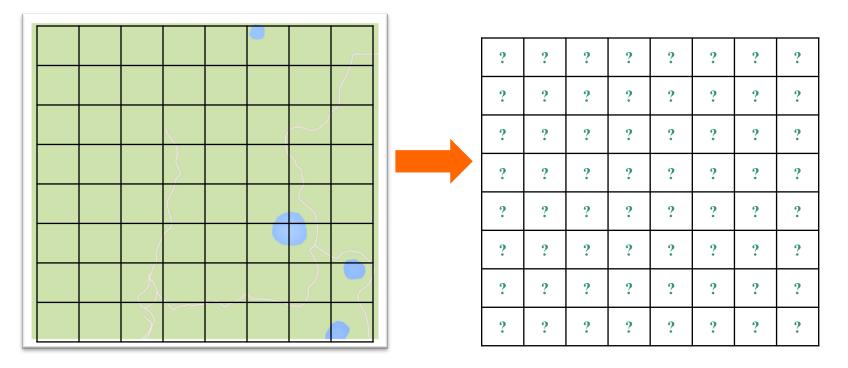
	Jan	Feb
Ν	80%	20%
S	20%	80%

Planning

□ Solve directly X

 \Box Optimize over all rounds \rightarrow computationally expensive

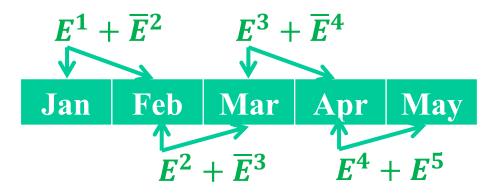
Jan Feb Mar Apr May



PlanAhead-M

□ PlanAhead-M

- Look ahead M steps: find an optimal strategy for current round as if it is the Mth last round of the game
- □ Sliding window of size M. Example with M=2



 \Box Add discount factor γ to compensate the over-estimation

PlanAhead-M

Algorithm 1 Plan Ahead(ω, M)Output: a defender strategy profile [c]1: for t=1 to T do2: $c^t = \text{f-PlanAhead}(c^{t-1}, \omega, \min\{T - t + 1, M\})$

□ Mathematical program

$$\max_{c^{t}, c^{t+1}, \dots, c^{t+m-1}} \sum_{\tau=0}^{m-1} E^{t+\tau}$$
(2)

s.t
$$E^{\tau} = \sum_{l} \sum_{i} q_{i}(\omega^{l}, \eta^{\tau}) U_{i}^{d}(c^{\tau}), \tau = t, .., t + m - 1$$
(3)

$$\eta^{\tau} = c^{\tau - 1}, \tau = t, .., t + m - 1$$
 (4)

$$\sum_{i} c_{i}^{\tau} \le K, \tau = t, .., t + m - 1$$
 (5)

□ Require the defender to execute the sequence of length M repeatedly

□ Example with M=2: find best strategy A and B

Jan	Feb	Mar	Apr	May
А	В	А	В	А

□ Theoretical guarantee: $\left(1 - \frac{1}{M}\right)$ approximation of the optimal strategy profile

FixedSequence-M

Algorithm 2 Fixed Sequence

Output: defender strategy profile [c]1: $(a^1, ..., a^M) = \text{f-FixedSequence}(\omega, M).$ 2: for t=1 to T do 3: $c^t = a^{(t \mod M)+1}$

$$\max_{a^1,...,a^M} \sum_{t=1}^M E^t$$
 (7)

s.t
$$E^t = \sum_l \sum_i q_i(\omega^l, \eta^t) U_i^d(a^t), t = 1, ..., M$$
 (8)

$$\eta^1 = a^M \tag{9}$$

$$\eta^t = a^{t-1}, t = 2, ..., M \tag{10}$$

$$\sum_{i} a_{i}^{t} \le K, t = 1, .., M$$
 (11)

Outline

Green Security Game Model

Planning algorithms

□ **Planning and Learning**

□ Results

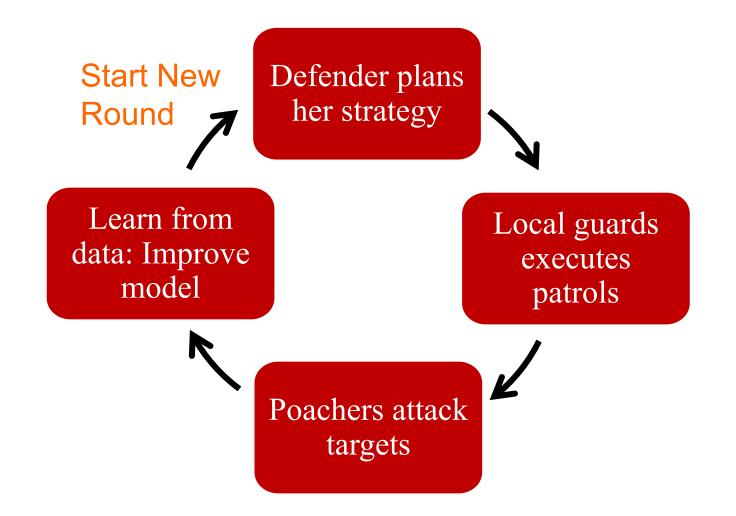
Planning and Learning

- Learn parameters in attackers' bounded rationality model from attack data
- Previous work
 - Apply Maximum Likelihood Estimation (MLE)
 - May lead to highly biased results
- Proposed learning algorithm
 - Calculate posterior distribution for each data point

Algorithm 3 Learn-BU $(\eta, \chi, \{\hat{\omega}\}, p)$

Output: \bar{p} - a probability distribution over $\{\hat{\omega}\} = \{\hat{\omega}^1, ..., \hat{\omega}^S\}$. 1: for *i*=1 to *N* do 2: for *s*=1 to *S* do 3: $\bar{p}_i(s) = \frac{p(s)q_i(\hat{\omega}^s, \eta)}{\sum_r p(r)q_i(\hat{\omega}^r, \eta)}$ 4: for *s*=1 to *S* do 5: $\bar{p}(s) = \frac{\sum_i \chi_i \bar{p}_i(s)}{\sum_i \chi_i}$

 χ_i - number of attacks on target i discrete set $\{\widehat{\omega}\}$ - $\{\widehat{\omega}^1, \dots, \widehat{\omega}^S\}$ prior p - $\langle p_1, \dots, p_S \rangle$ **General Framework of Green Security Game**



Outline

Green Security Game Model

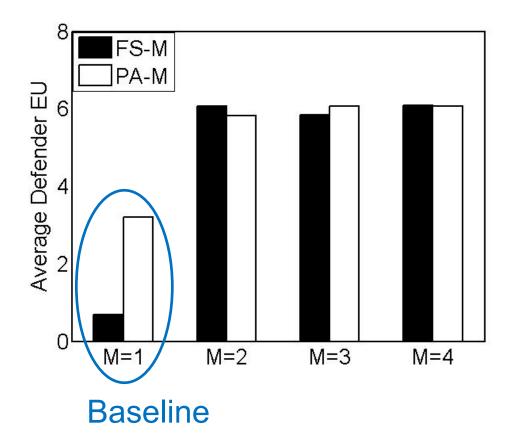
Planning algorithms

Planning and Learning



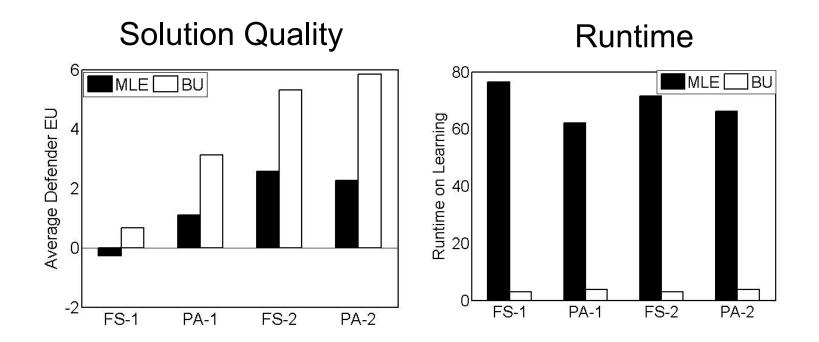
Experimental Results Planning

- Baseline: FS-1 (Stackelberg), PA-1 (Myopic)
- Attacker respond to last round strategy, 10 Targets, 4 Patrollers



Experimental Results Planning and Learning

Baseline: Maximum Likelihood Estimation (MLE)



Thank you!