Game Theory and Security

Human Behavior Modeling & Learning

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Wildlife Population Threatened by Poaching

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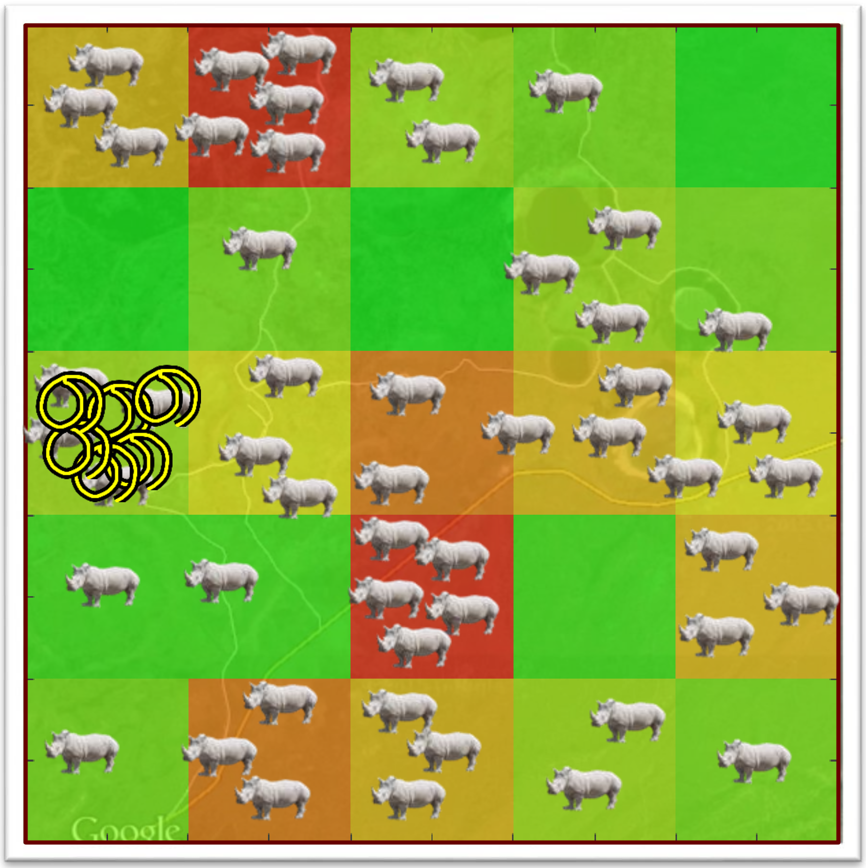
Wildlife Population Threatened by Poaching

- Get the most out of the patrols
  - Game theory + machine learning

Challenges in Wildlife Conservation

- Frequent and repeated attacks
  - Not one-shot
- Attacker decision making
  - Limited surveillance / Less effort / Boundedly rational
- Real-world data
  - Sparse / Incomplete / Uncertainty / Noise
- Real-world deployment
  - Practical constraints
  - Field test

- Perfectly rational (Maximize expected utility)? No!



Challenges in Wildlife Conservation

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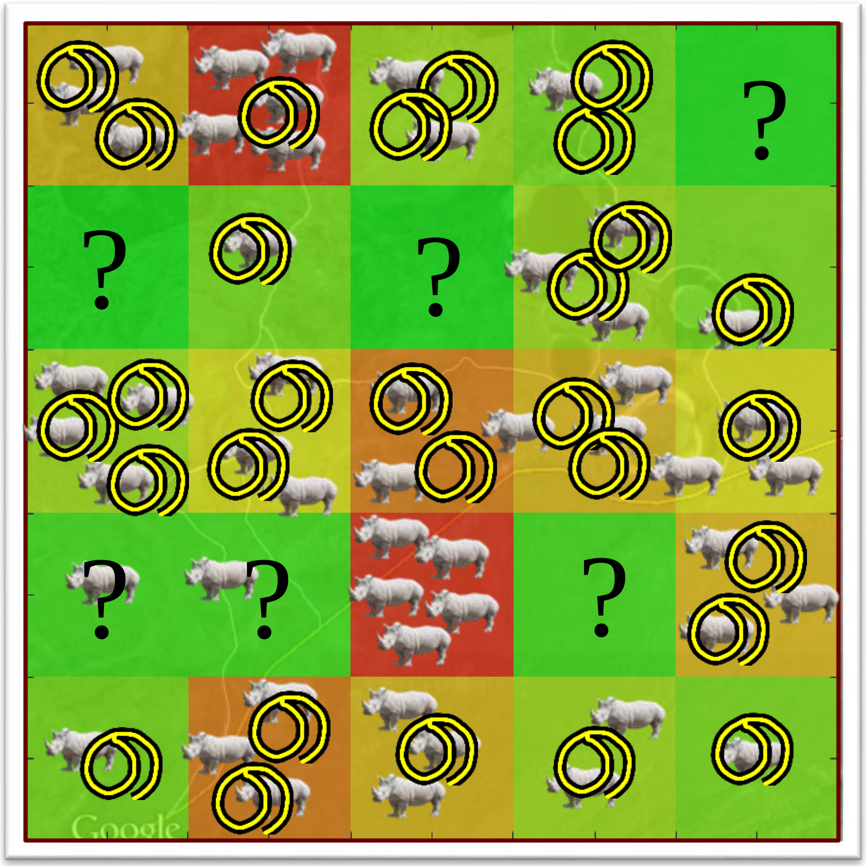

Human Behavior Modeling & Learning

- Uncertainty and Bias Based Models
  - Prospect Theory [Kahneman and Tvesky, 1979]
  - Anchoring bias and epsilon-bounded rationality [Pita et al, 2010]
  - Attacker aims to reduce the defender's utility [Pita et al, 2012]
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PT: Prospect Theory

- Model human decision making under uncertainty
- Maximize the 'prospect' [Kahneman and Tvesky, 1979]

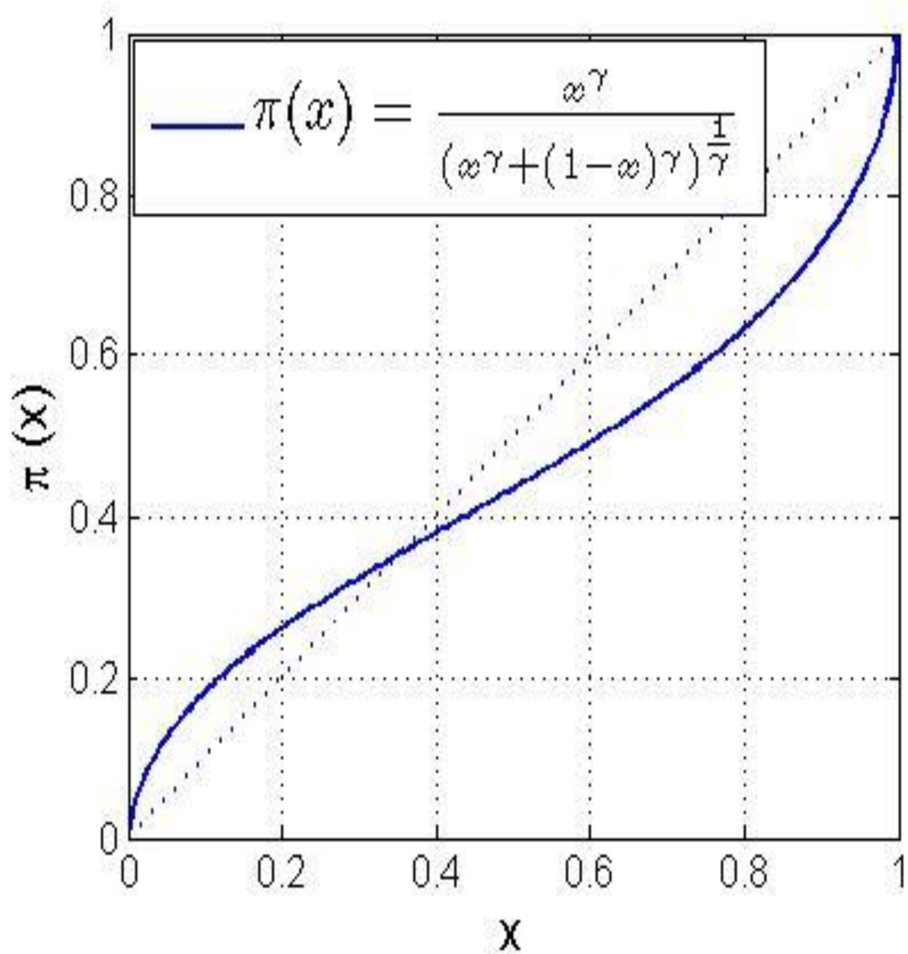
$$\text{prospect} = \sum_{i \in AllOutcomes} \pi(x_i) \cdot V(C_i)$$

  - π(·): weighting function
  - V(·): value function
- Defender: choose a strategy that maximizes DefEU when attacker best responds to the expected prospect (instead of AttEU)

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica: Journal of the econometric society, 263-291.

PT: Prospect Theory

- Empirical Weighting Function
- Slope gets steeper as x gets closer to 0 and 1
- Not consistent with probability definition
  - $\pi(x)+\pi(1-x) < 1$
- Empirical value: $\gamma=0.64$ $(0<\gamma<1)$



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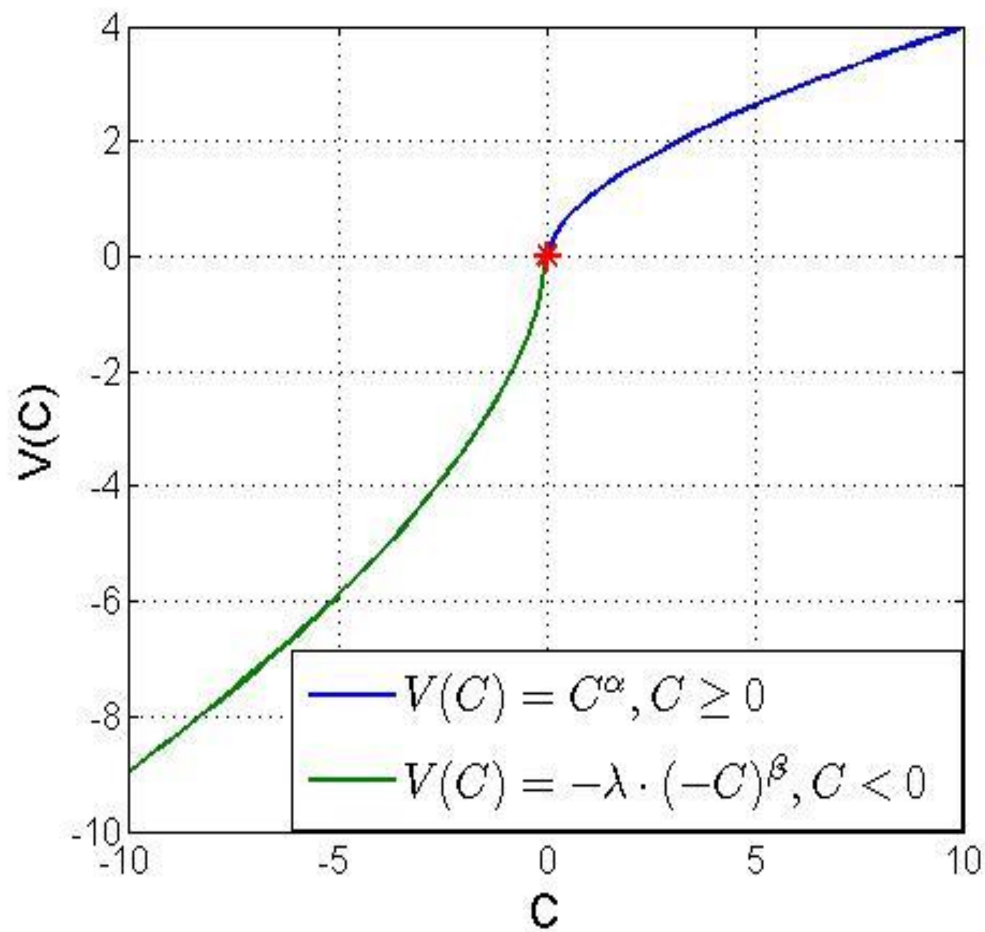
PT: Prospect Theory

- Empirical Value Function
- Risk averse regarding gain
- Risk seeking regarding loss
- Empirical value: $\alpha=\beta=0.88$, $\lambda=2.25$



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COBRA: Anchoring Bias and Epsilon-Bounded Rationality

- "epsilon optimality"
- Anchoring bias: Full observation ($\alpha = 0$) vs no observation ($\alpha = 1$)

$$\max_{x,q,\gamma,a} \gamma$$

$$s.t.\ x' = (1-\alpha)x + \frac{\alpha}{N}$$

a is attacker's highest expected utility given x'

$q_j = 1$ if $\mathrm{AttEU}_j(x') \geq a - \epsilon$

$\gamma \leq \mathrm{DefEU}_j(\mathrm{x})$ if $q_j = 1$

- Experiments: $\alpha = 0.37$ works best

Pita et al. Effective solutions for real-world stackelberg games: When agents must deal with human uncertainties. In AAMAS, 2009.

MATCH: Attacker aims to reduce the defender's utility

- Attacker may deviate from the best response to reduce the defender's expected utility
- Choose a target to maximize

$$\frac{\text{Defender's utility loss due to deviation}}{\text{Adversary's utility loss due to deviation}}$$

- Defender: choose a strategy that maximize DefEU while bound the above value by β
- Experiments: $\beta = 1$

Pita et al. A robust approach to addressing human adversaries in security games. In ECAI, 2012

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QR: Quantal Response Model

- Error in individual's response
  - Still: more likely to select better choices than worse choices
- Probability distribution of different responses
- Quantal best response:

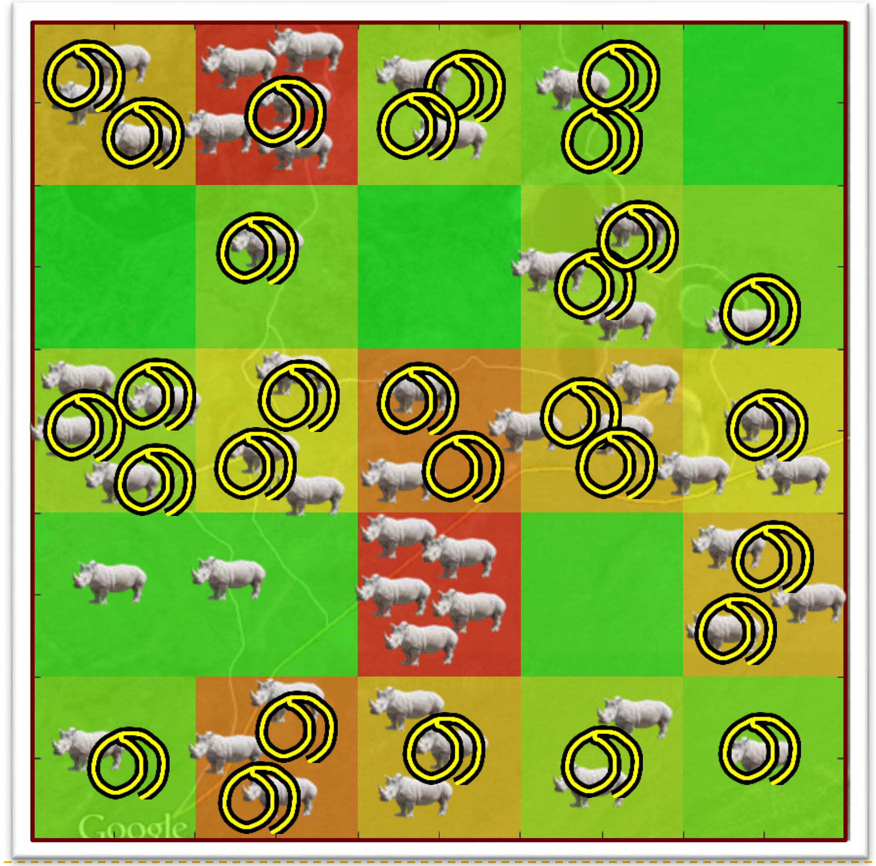
$$q_j = \frac{e^{\lambda * \mathrm{AttEU}_j(x)}}{\sum_i e^{\lambda * \mathrm{AttEU}_i(x)}}$$

- λ: represents error level (=0 means uniform random)
  - Maximal likelihood estimation (λ=0.76)

McKelvey, R. D., & Palfrey, T. R. (1995). Quantal response equilibria for normal form games. Games and economic behavior, 10(1), 6-38.

SUQR: Subjective Utility Quantal Response Model

- $\mathrm{SEU}_j = \sum_k w_k * f_j^k, \;\; q_j = \frac{e^{\lambda * \mathrm{SEU}_j(x)}}{\sum_i e^{\lambda * \mathrm{SEU}_i(x)}}$



Coverage Probability
+ Reward/Penalty

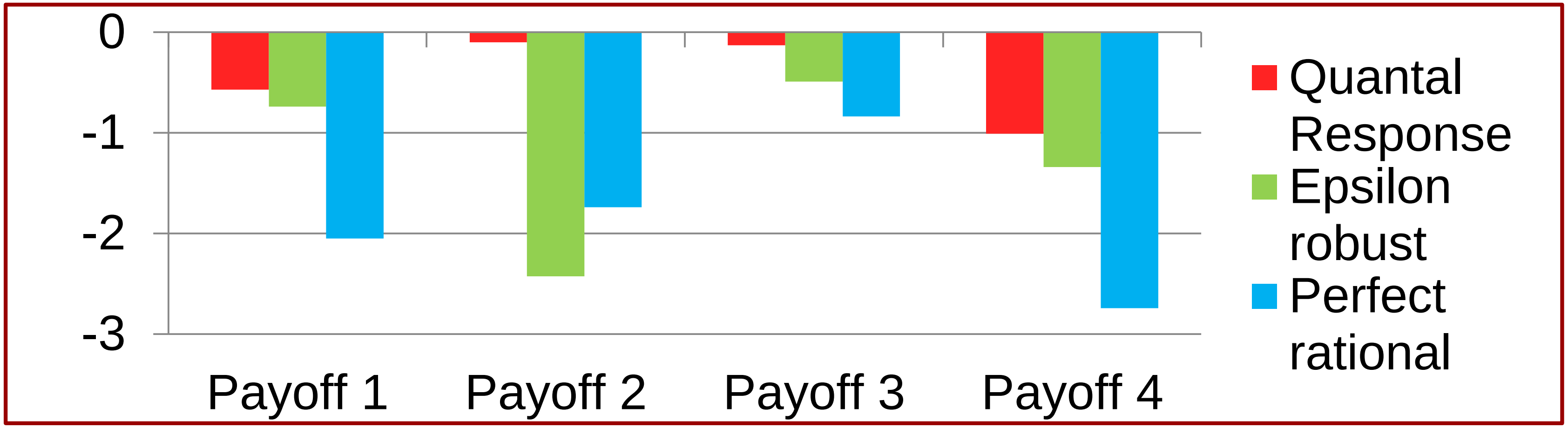
SUQR

Attack Probability

Nguyen, T. H., Yang, R., Azaria, A., Kraus, S., & Tambe, M. Analyzing the Effectiveness of Adversary Modeling in Security Games. In AAAI, 2013.

Comparison of Model Performance

- Prospect Theory < DOBSS < COBRA < Quantal Response < MATCH < SUQR



MATCH wins	Draw	QR wins
42	52	6

MATCH wins	Draw	SUQR wins
1	8	13

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GSG: Incorporating Delayed Observation

Wildlife

Forest

Fishery

- Frequent and repeated attacks
  - Not one-shot / More data
- Attacker decision making
  - Limited surveillance / Less effort / Boundedly rational
- New model: Green Security Games

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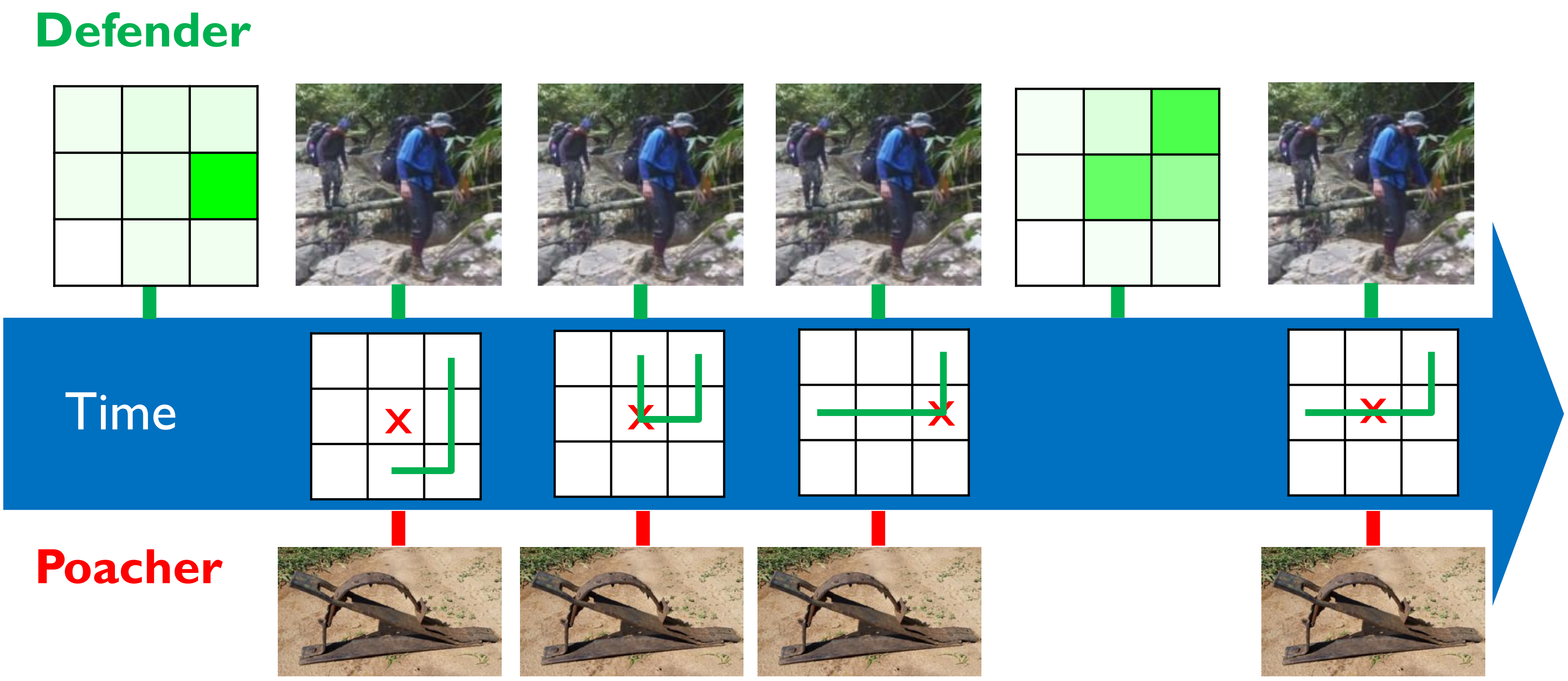

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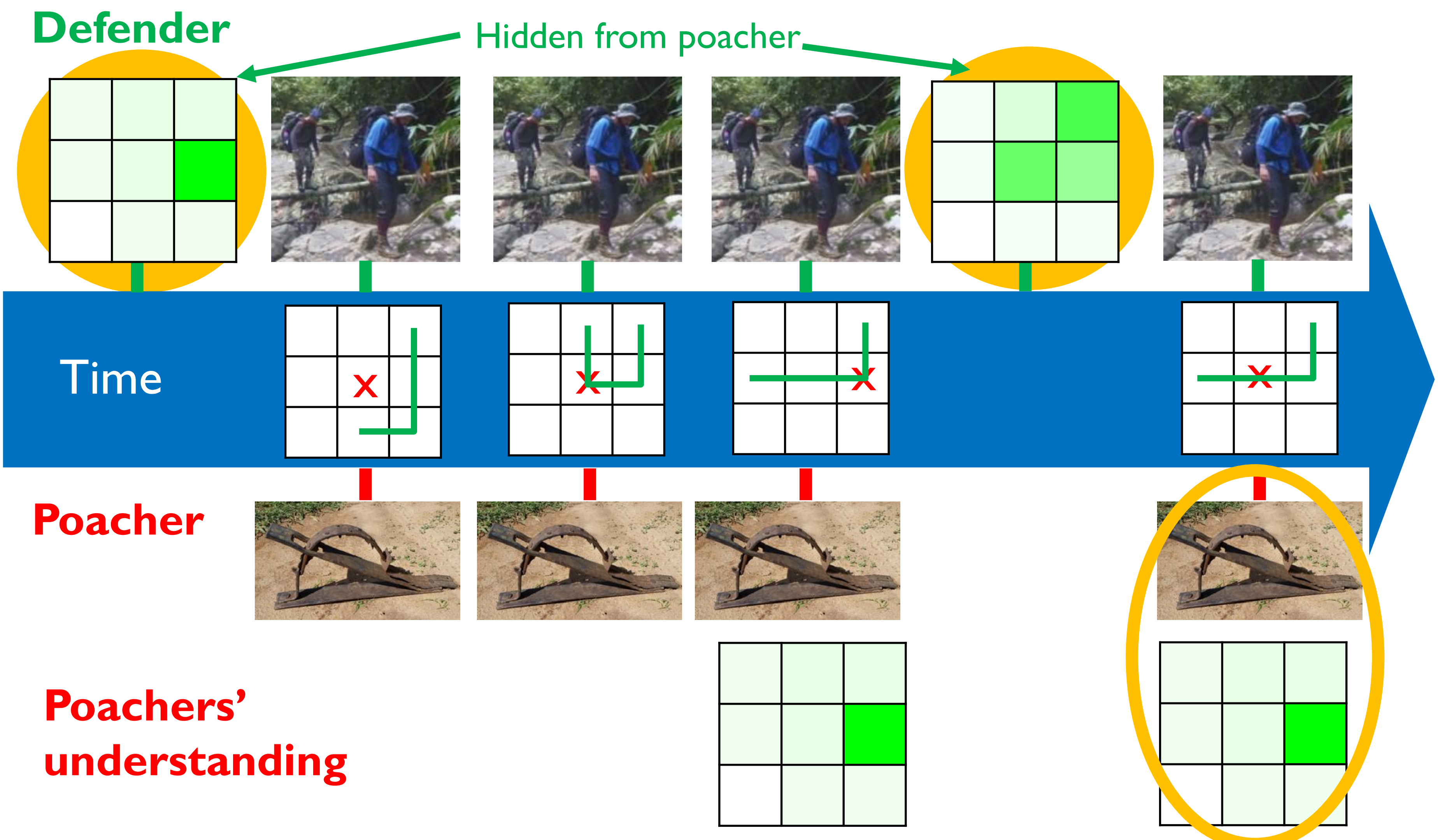

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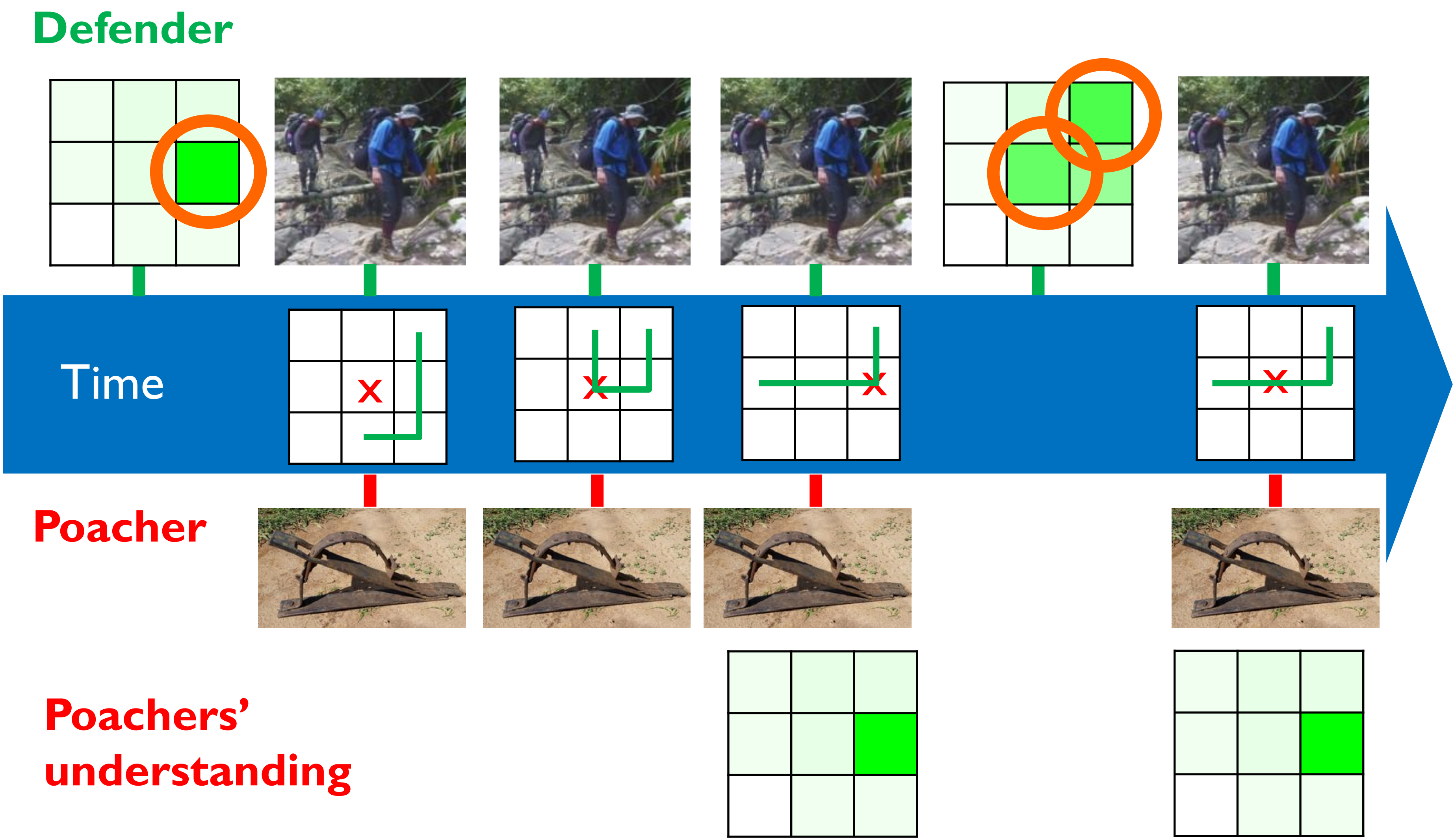

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GSG: Incorporating Delayed Observation

- A Green Security Game (GSG) is a T stage game where the defender protects N targets against L attackers. Defender chooses a mixed strategy c^t in stage t.
- A GSG attacker is characterized by his memory length Γ, coefficients $\alpha_0, \ldots, \alpha_\Gamma$ and SUQR model parameter ω. In stage t, he responds to a convex combination of defender strategy in recent $\Gamma + 1$ rounds: $\eta_t = \sum_{\tau=0}^{\Gamma} \alpha_\tau c^{t-\tau}$

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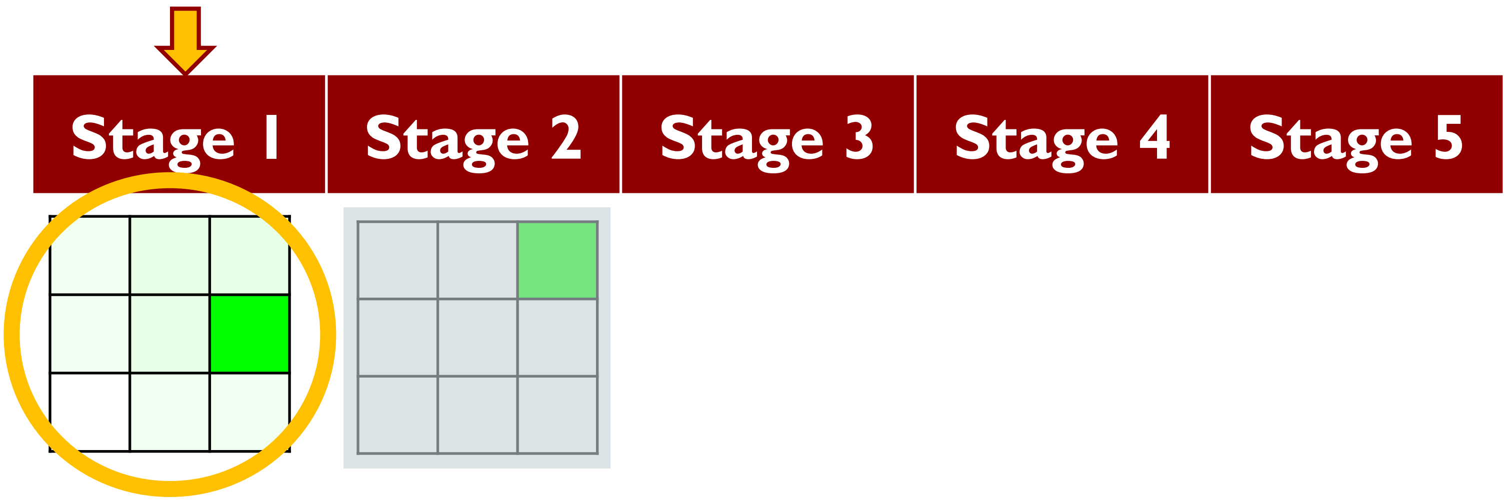
GSG: Incorporating Delayed Observation

- Plan Ahead – M (PA-M)
- Plan ahead M stages



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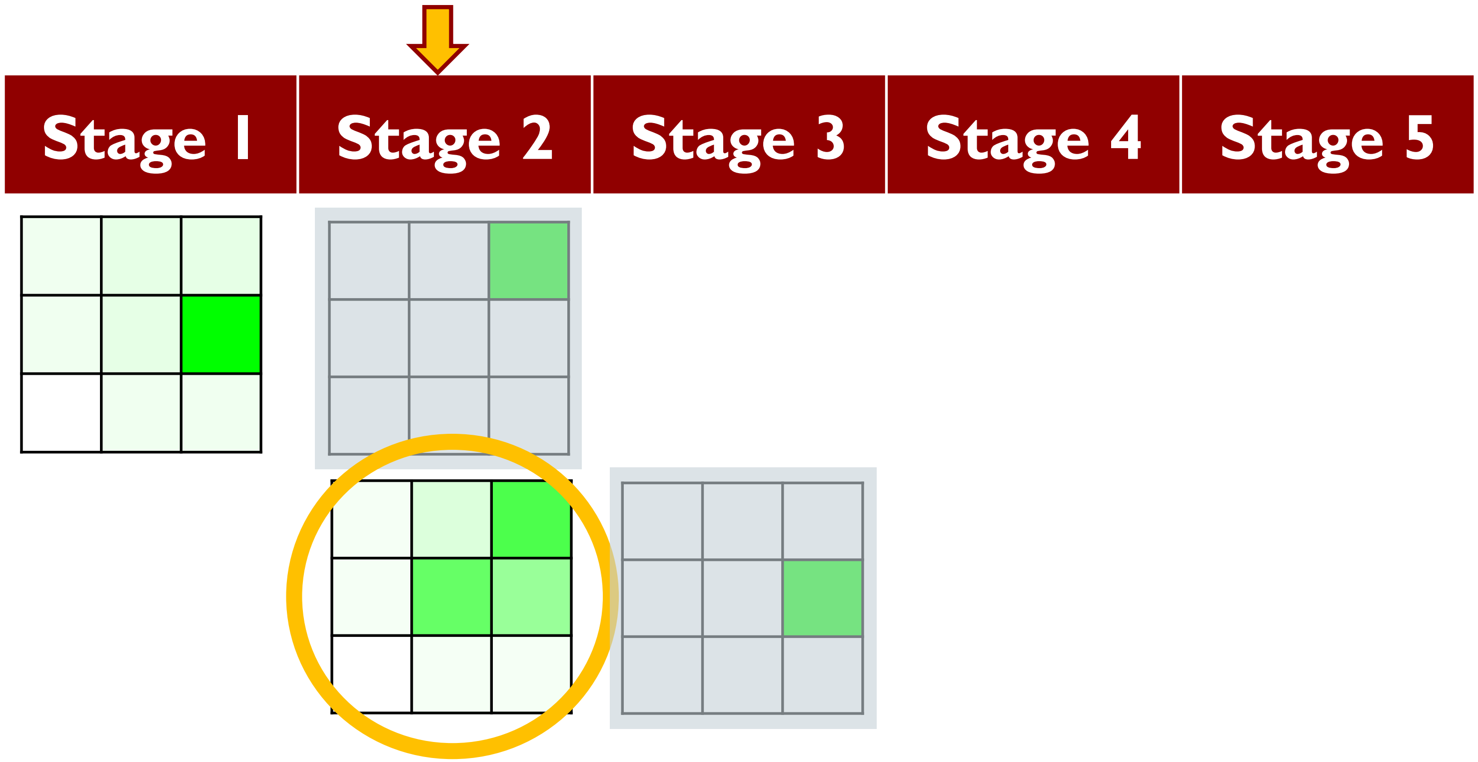

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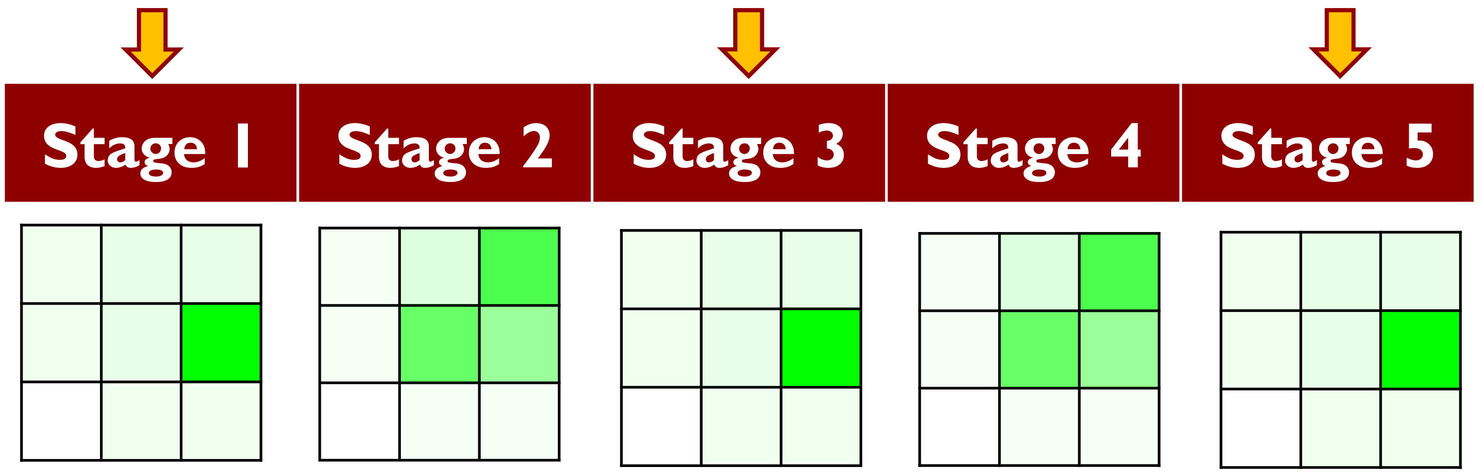
GSG: Incorporating Delayed Observation

- An alternative: Fixed Sequence – M (FS-M)
- Use M strategies repeatedly



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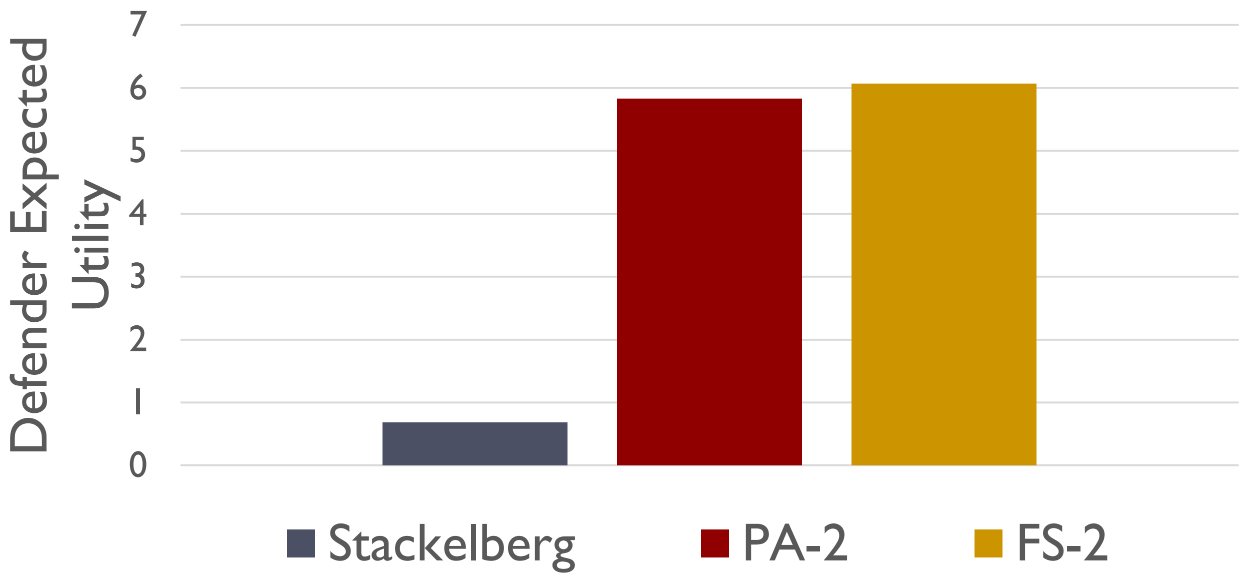

- **Theorem 3**: In a GSG with T rounds, for $\Gamma < \mathrm{M} \leq T$, there exists a cyclic defender strategy profile $[s]$ with period M that is a $(1 - \frac{\Gamma}{T})\frac{Z-1}{Z+1}$ approximation of the optimal strategy profile in terms of the normalized utility, where $Z = \left\lfloor \frac{T-\Gamma+1}{M} \right\rfloor$

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SHARP: Bounded Rationality in Repeated Games

Kar, D., Fang, F., Delle Fave, F., Sintov, N., & Tambe, M. A game of thrones: when human behavior models compete in repeated Stackelberg security games. In AAMAS, 2015

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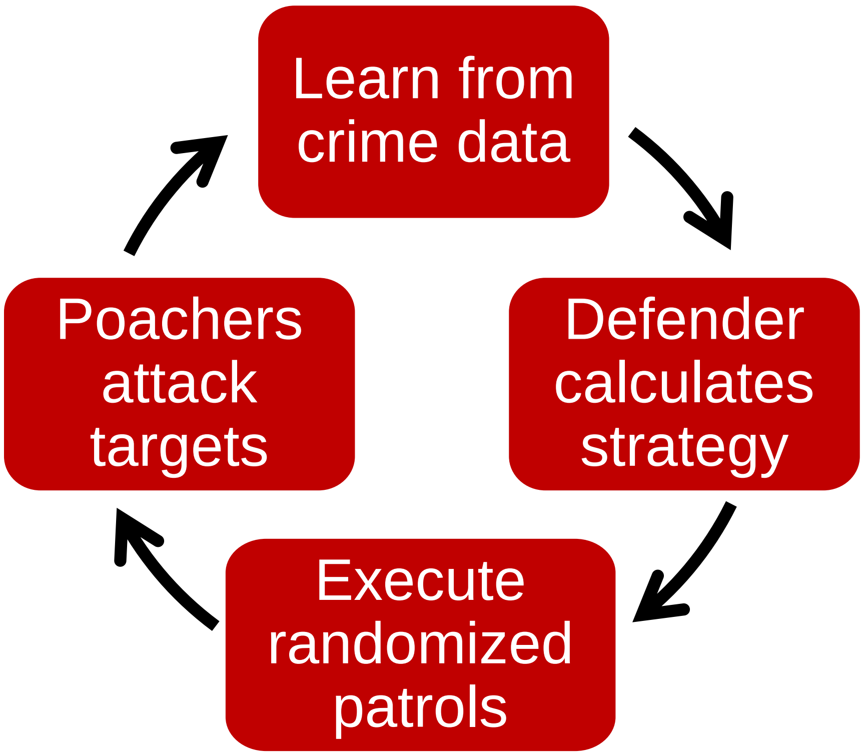
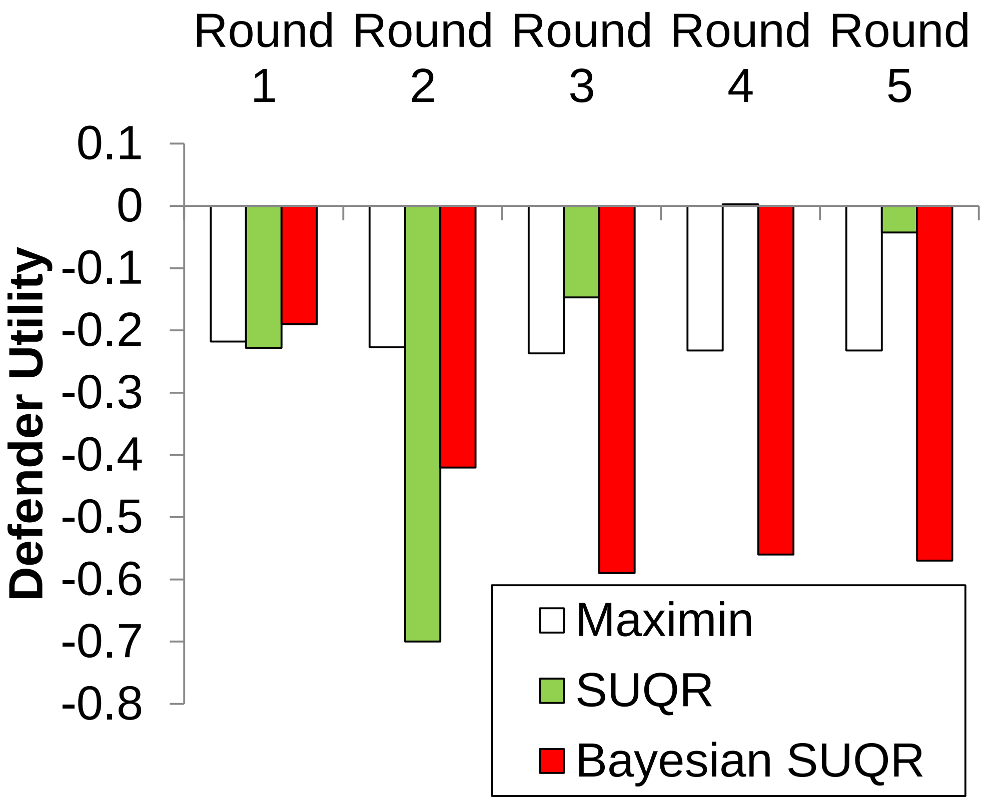


Repeated games on AMT: 35 weeks, 40 human subjects 10,000 emails!



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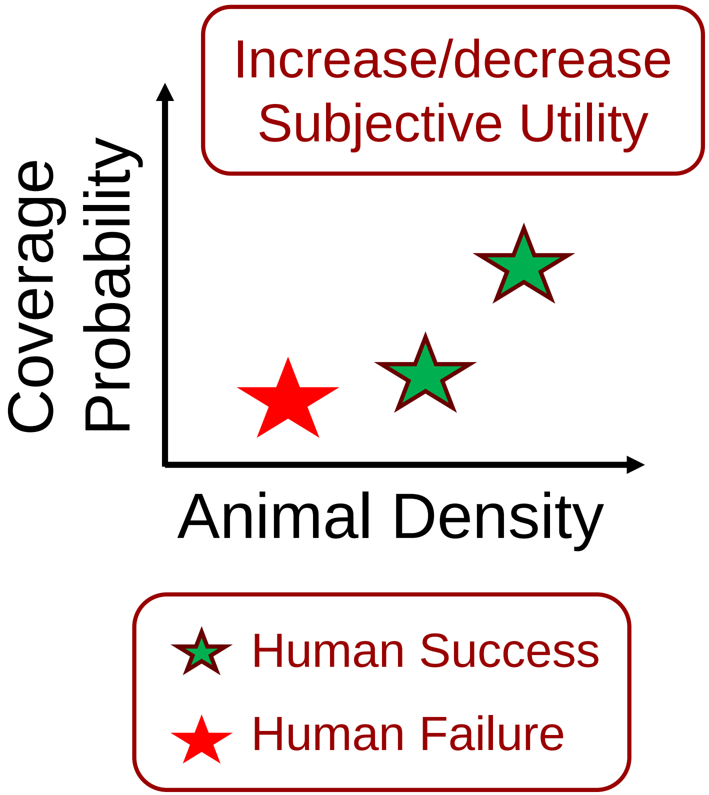

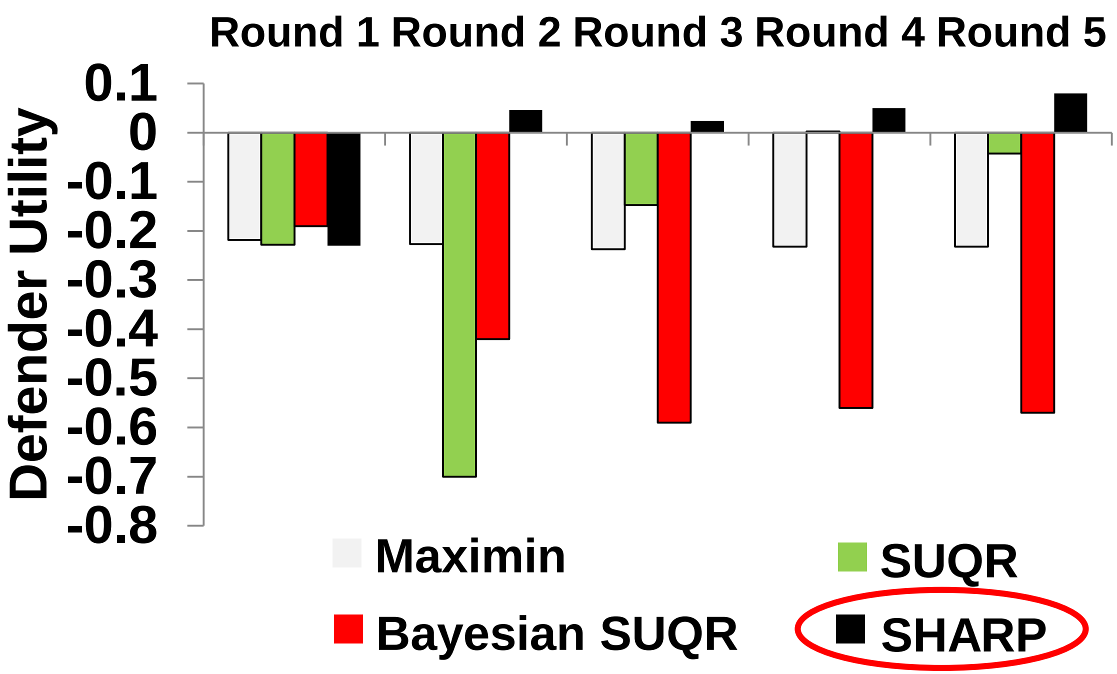

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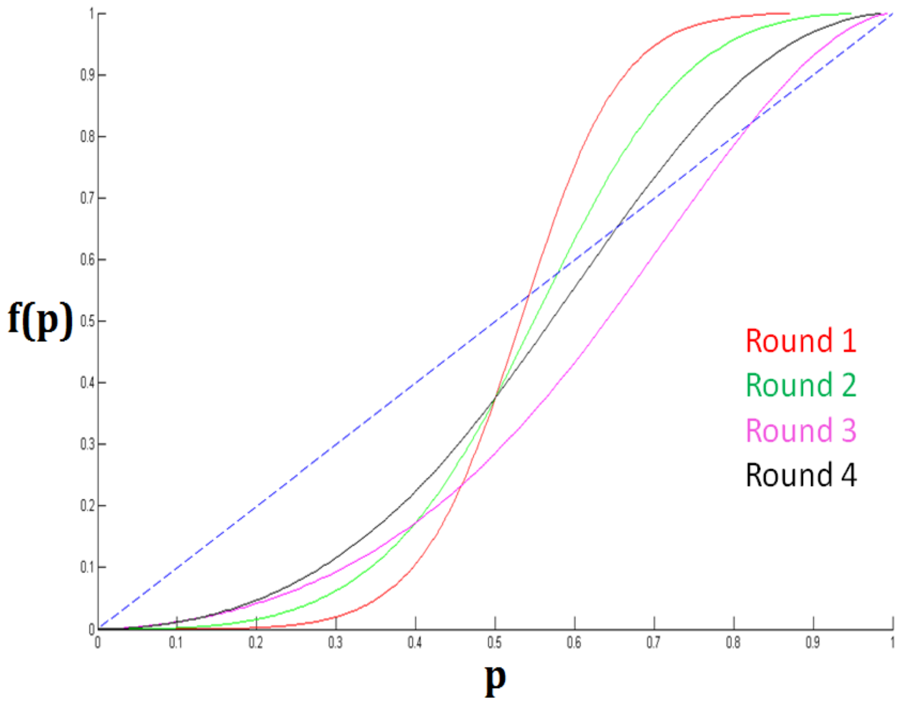
SHARP: Bounded Rationality in Repeated Games

- Adversary's probability weighting function is S-shaped.
  - Contrary to Prospect Theory



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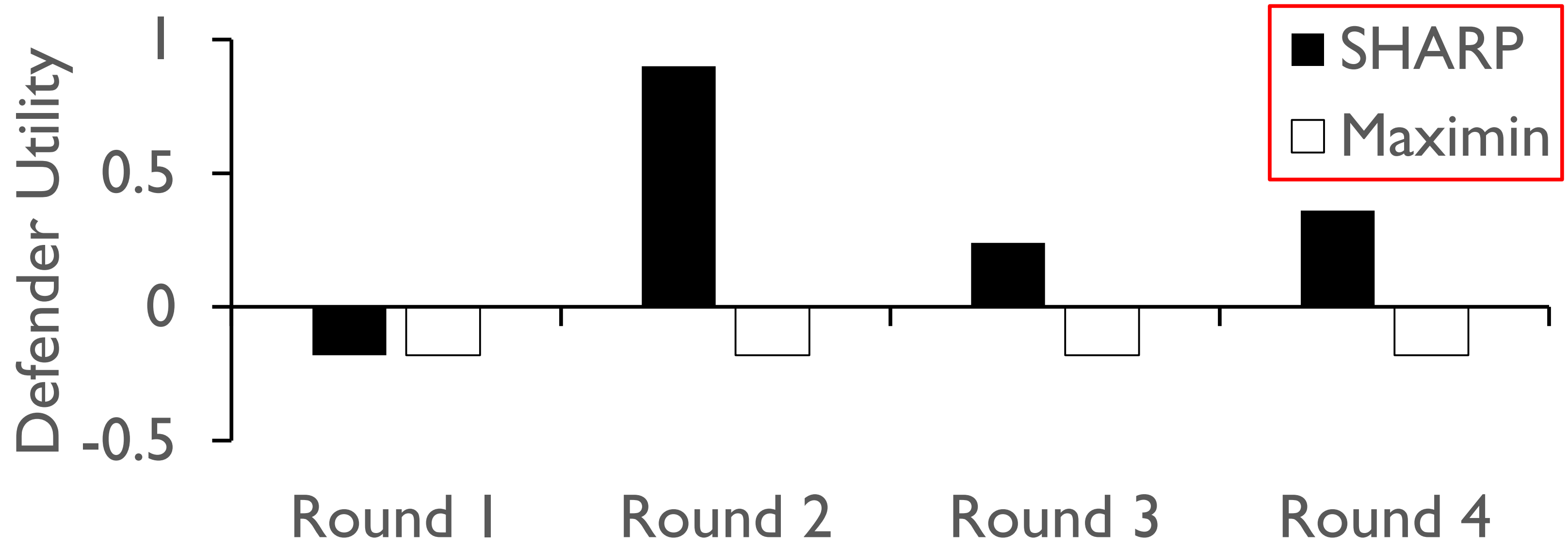

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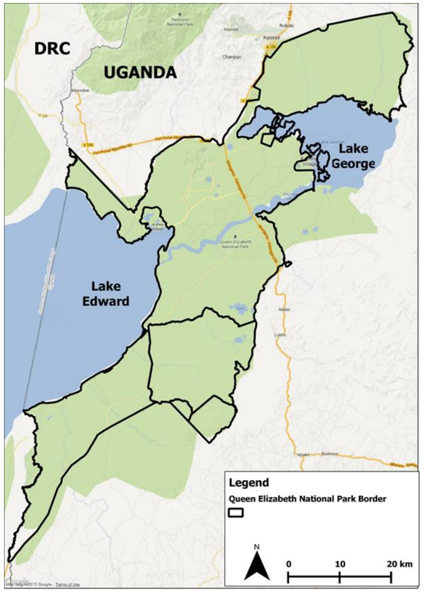
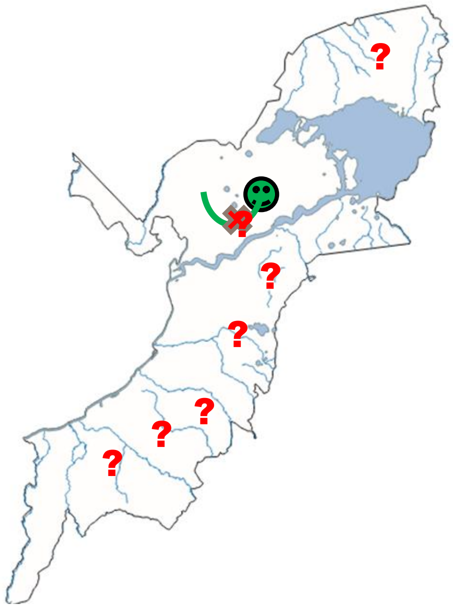
Real-World Data

- Queen Elizabeth National Park
  - 1,978 sq. km
  - 2003-2015
- Geospatial Features
  - Terrain (e.g., forest, slope)
  - Distance to {Town, Water, Outpost}
- Ranger Coverage
- Crime Observations



Real-World Data: Challenges

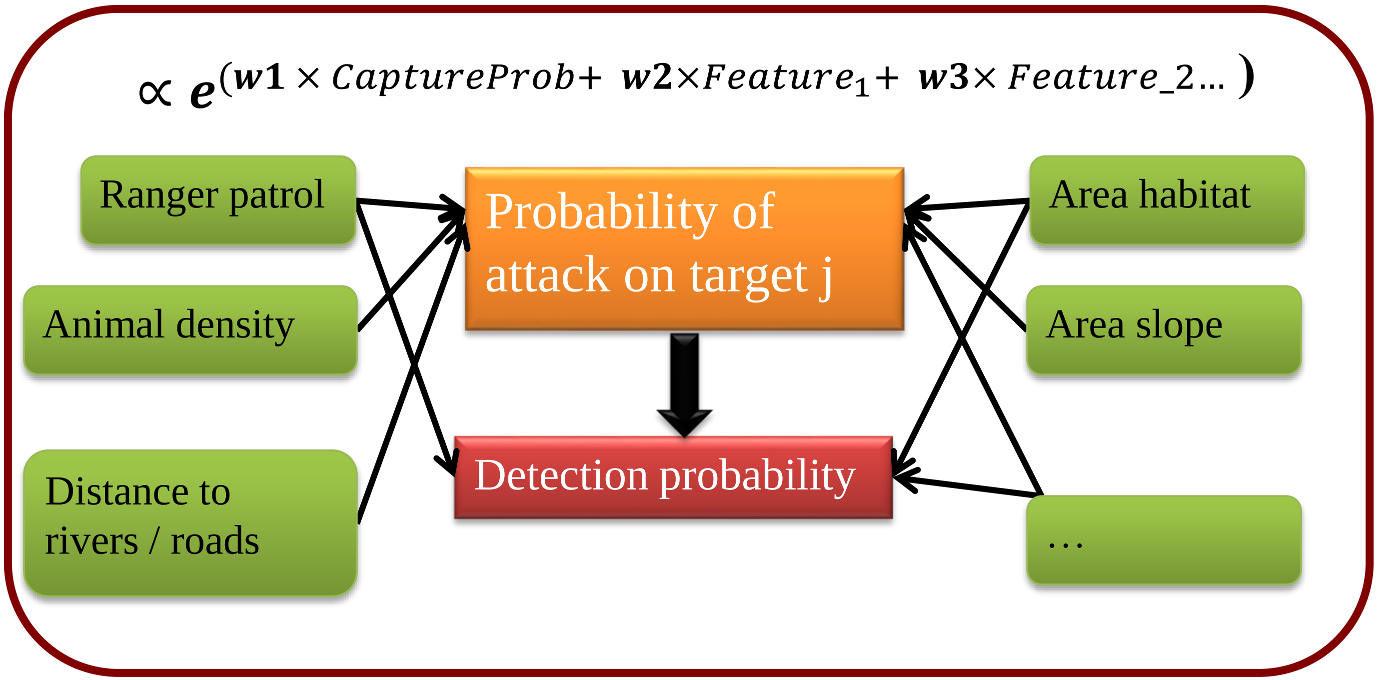
- "Missing" poaching data
  - Limited patrol resources (silent victims)
  - Imperfect observations (e.g., hidden snares)



- Consequences
  - Uncertainty in negative labels
  - Class imbalance

Nguyen et al. Capture: A new predictive anti-poaching tool for wildlife protection. In AAMAS, 2016

CAPTURE: Two-Layered Model



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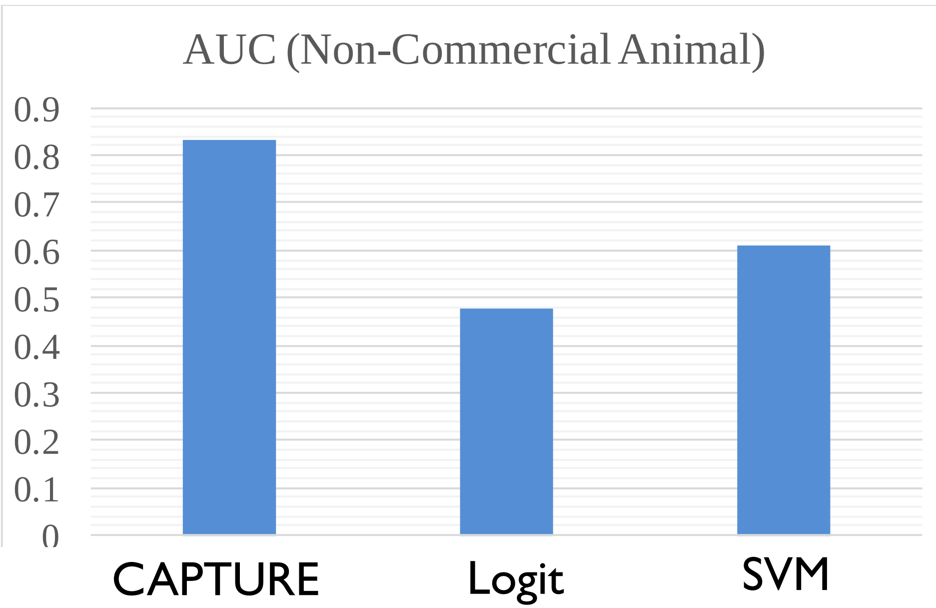
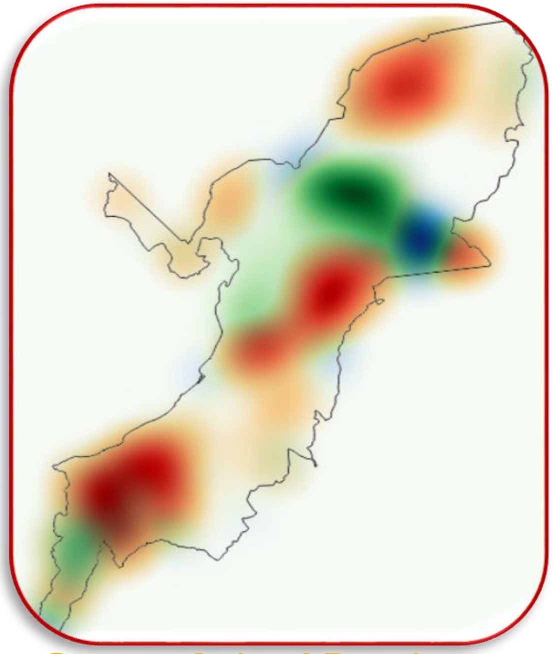


Dry Season (June-August 2008)



Green – Animal Density;

Blue – Defender Strategy;

Red – Observed Attack Probability

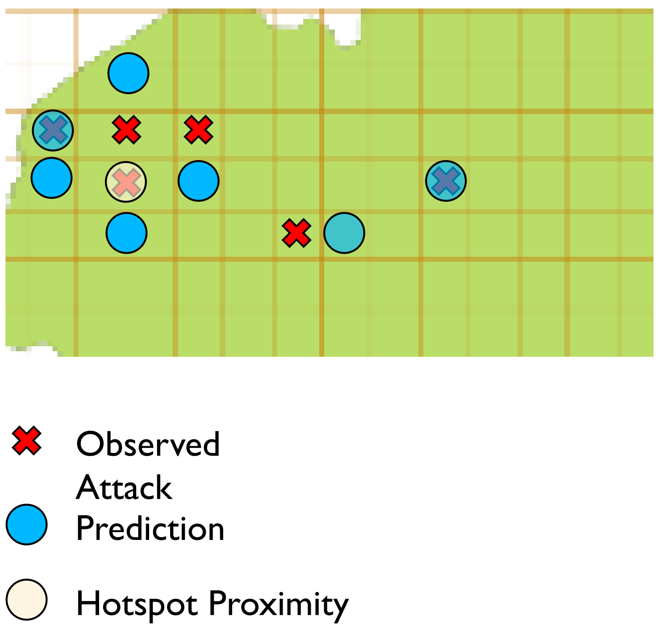
Nguyen et al. Capture: A new predictive anti-poaching tool for wildlife protection. In AAMAS, 2016

CAPTURE: Two-Layered Model

- Limitations
  - Limited Data
  - Predicting Everywhere
  - Slow Learning
- Variations
  - Simpler observation layer
  - Use previous coverage instead of current coverage
  - Exponentially penalize the attractiveness of inaccessible areas
  - No improvement

INTERCEPT: Decision-Tree Based Model

- BoostIT
- Consider spatial correlations (hotspots)
  - Learn a decision tree
  - Compute predictions
  - Hotspot proximity computation
  - Learn a new decision tree with hotspot proximity as a feature
  - Repeat until a stopping condition is reached



Kar & Ford et al. Cloudy with a Chance of Poaching: Adversary Behavior Modeling and Forecasting with Real-World Poaching Data. In AAMAS , 2017

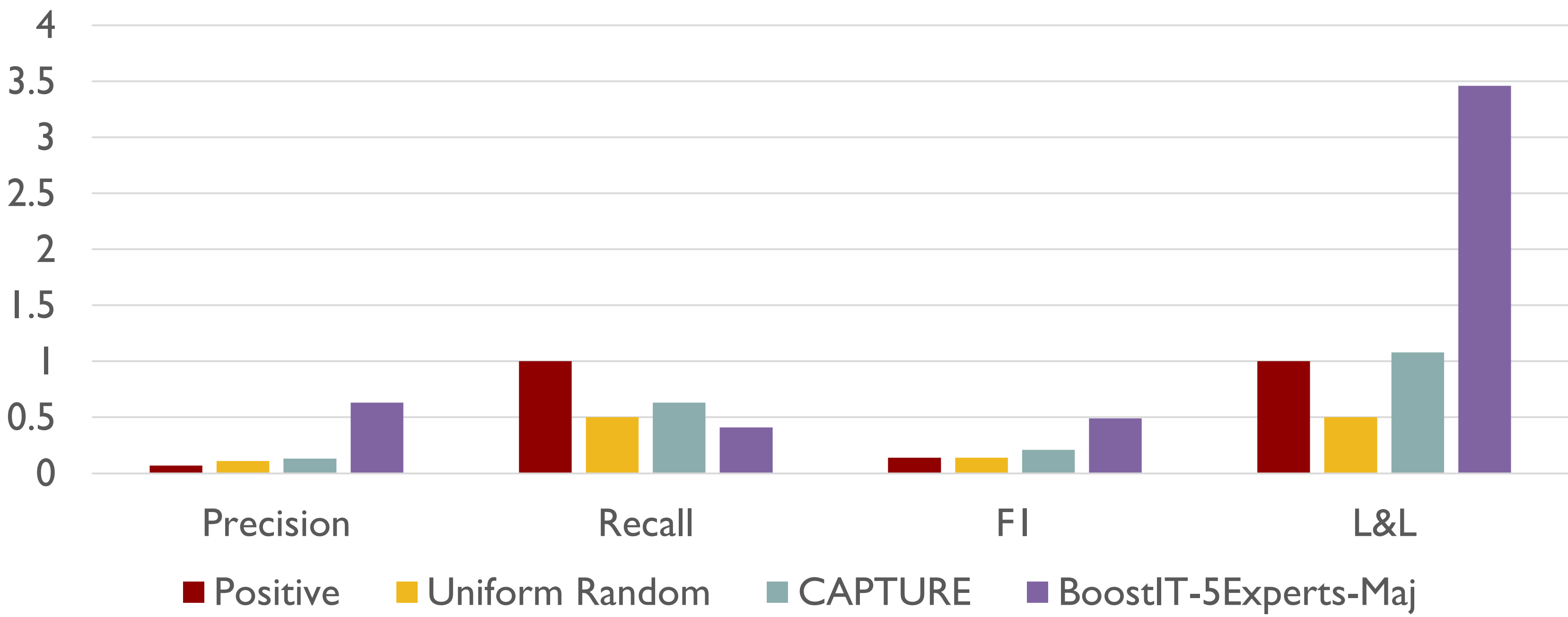
INTERCEPT: Decision-Tree Based Model

- Extensive Empirical Evaluation
  - 40 models w/ total of **192 model variations**
  - Decision tree ensemble outperforms all other (complex) models including CAPTURE
    - Standard decision tree, 2 BoostITs (α =2, 3), 2 Decision Trees (FP cost = 0.6, 0.9)
  - Fast runtime and interpretability led to its deployment (obstacles for CAPTURE)

- Datasets
  - Trained: 2003-2014, Tested: 2015
  - Trained: 2003-2013, Tested: 2014

INTERCEPT: Decision-Tree Based Model

Empirical Evaluation: Key Attack Prediction Results: 2015

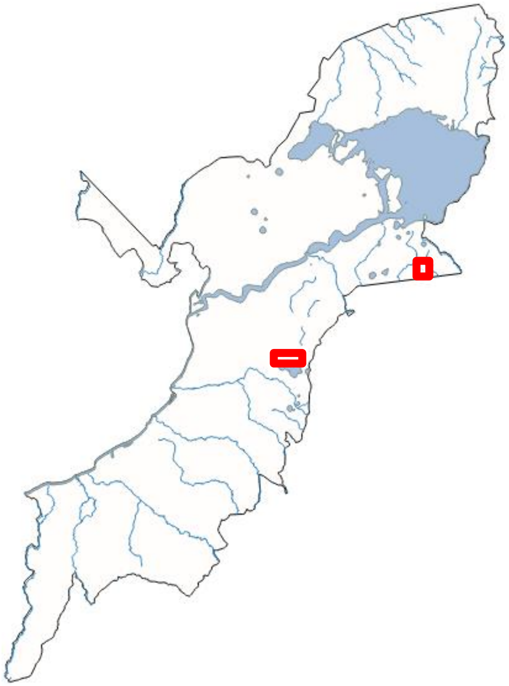


$$\boxed{L\&L(D, T_e) = \frac{recall^2}{\Pr[f(T_e) = 1]}}$$

Kar & Ford et al. Cloudy with a Chance of Poaching: Adversary Behavior Modeling and Forecasting with Real-World Poaching Data. In AAMAS , 2017

Real-world Deployment: Field Test 1 (1 month)

- Trespassing
  - 19 signs of litter, ashes, etc.
- Poached animals
  - 1 poached elephant
- Snaring
  - 1 active snare
  - 1 cache of 10 antelope snares
  - 1 roll of elephant snares
- Snaring hit rates
  - Outperform 91% of months



Historical Base Hit Rate	Our Hit Rate
Average: 0.73	3

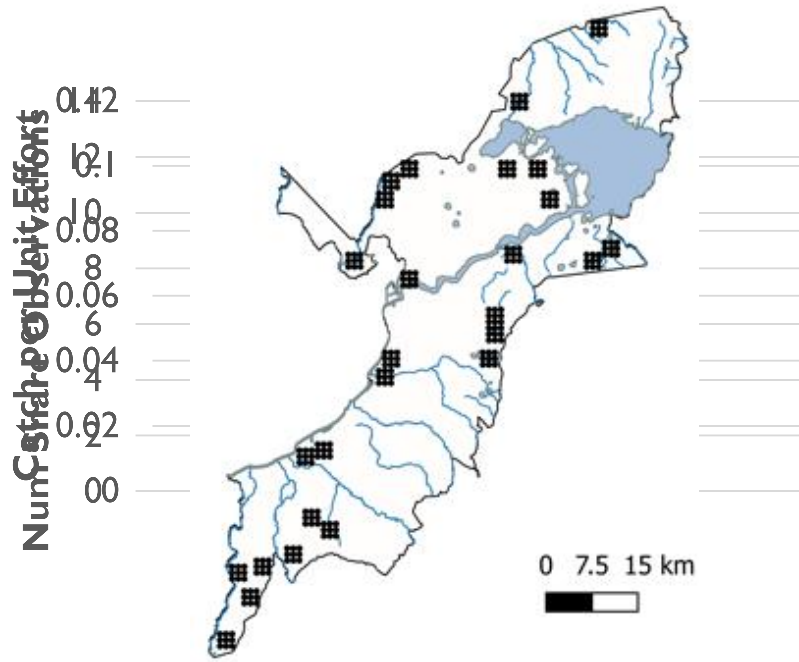
Kar & Ford et al. Cloudy with a Chance of Poaching: Adversary Behavior Modeling and Forecasting with Real-World Poaching Data. In AAMAS , 2017

Real-world Deployment: Field Test 2 (5 months)

- 27 areas (9-sq km each)
- 454 km patrolled in total

- 2 experiment groups
  - 1: >= 50% attack prediction rate
    - 5 areas
  - 2: < 50% attack prediction rate
    - 22 areas

- Catch Per Unit Effort (CPUE)
  - Unit Effort = km walked



 Gholami & Ford et al. Taking it for a Test Drive: A Hybrid Spatio-temporal Model for Wildlife Poaching Prediction Evaluated through a Controlled Field Test. In ECML, 2017

Deployment Results Summary

- First Field Test: Demonstrated potential for predictive analytics in the field
- Second Field Test: Demonstrated the selectiveness of our model in the field
- <u>We saved animals</u>!

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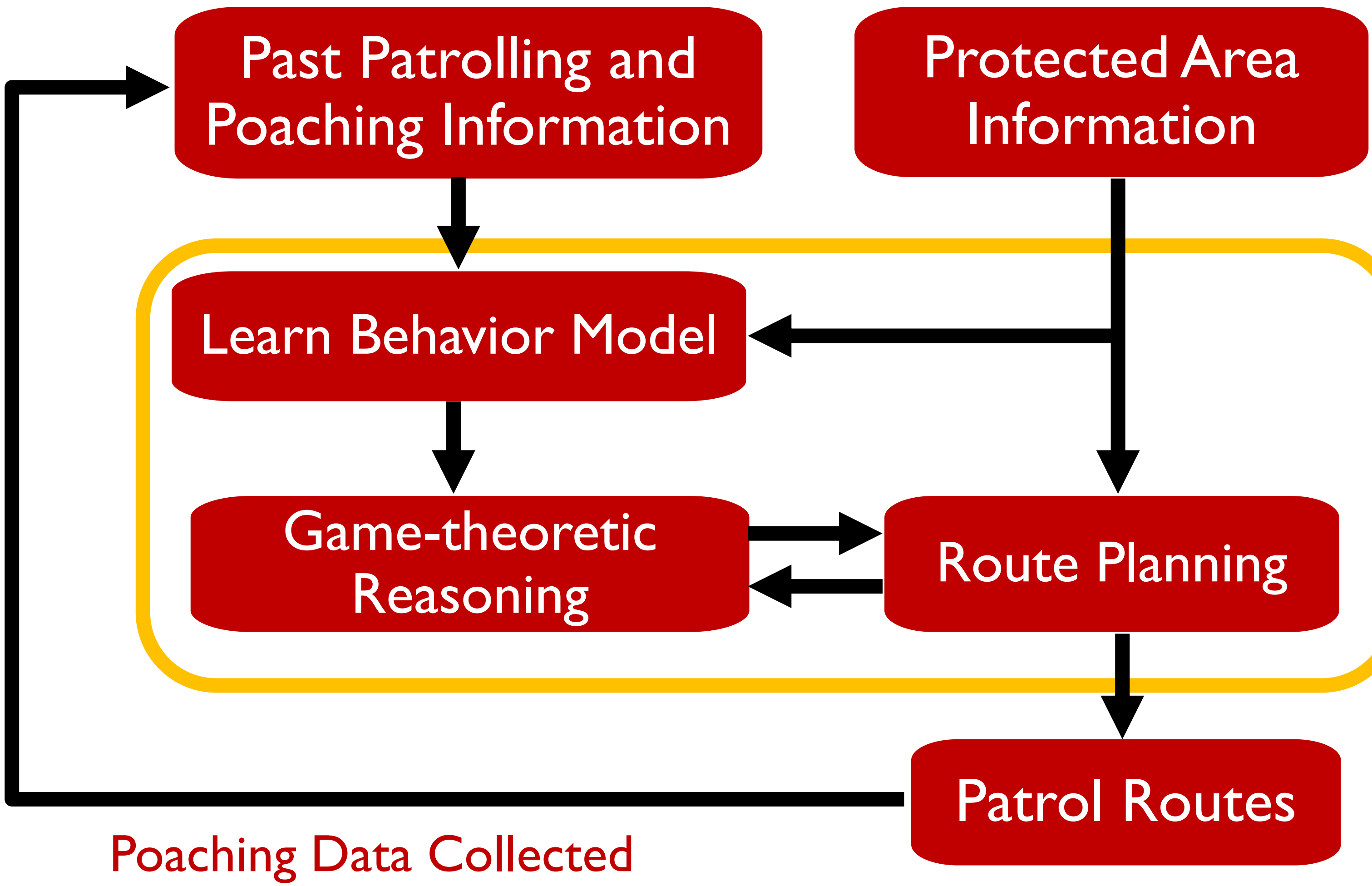
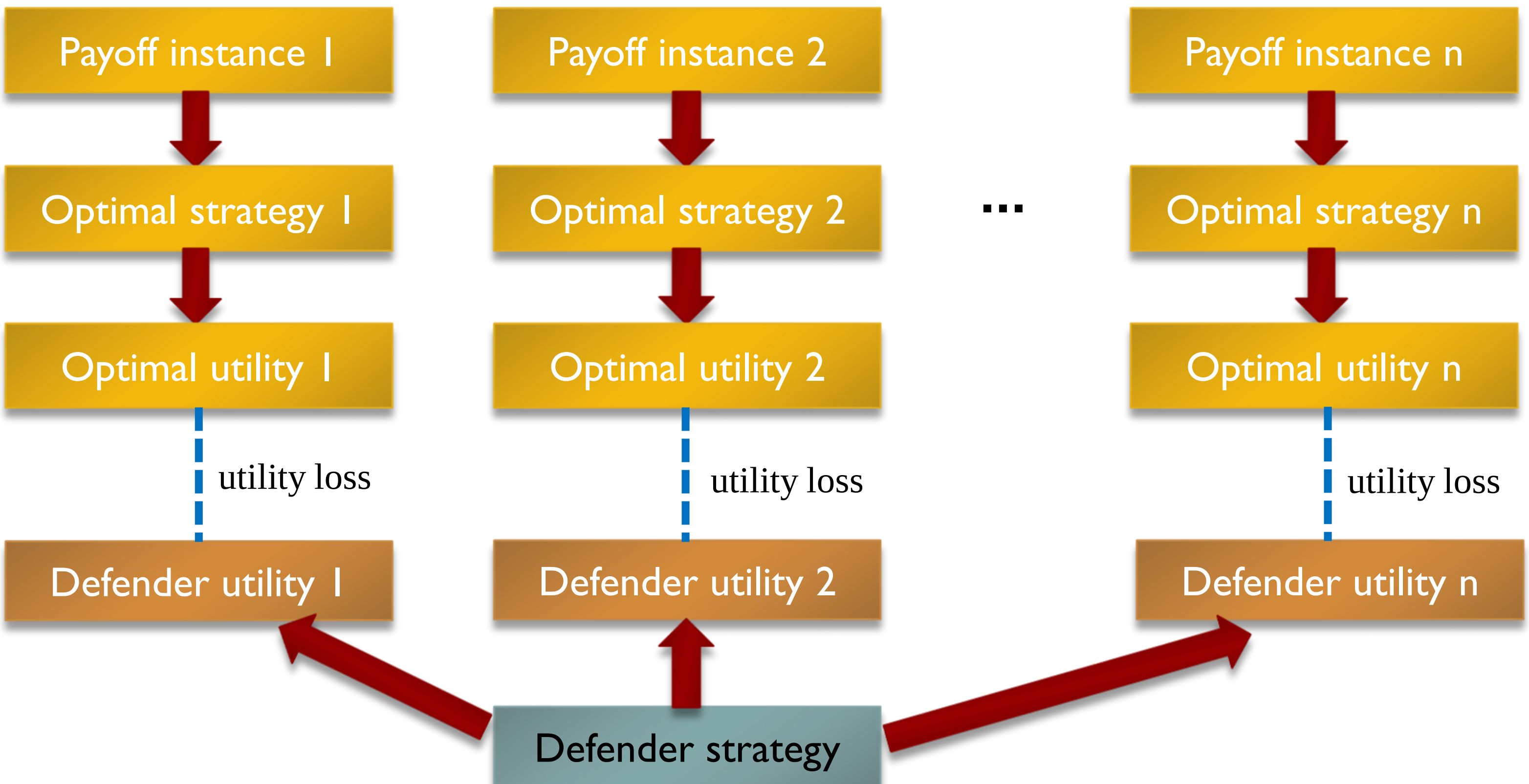
PAWS Overview



Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Component: Game-theoretic Reasoning

- Handling payoff uncertainty
- Behavioral minimax regret [Nguyen et al, 2016]



Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- Uncertainty interval

Adversary

Defender	Target 1	Target 2
Target 1	4, [-4, -2]	-1, [0, 2]
Target 2	-5, [4, 6]	2, [-2, 0]

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- Defender's utility of playing "x" given payoff instance
  - Sampled one payoff instance from interval

- defUtility(x) = -0.5

Adversary

Defender

	Target 1	Target 2	x
Target 1	4, -4	-1, 1	0.3
Target 2	-5, 5	2, -2	0.7
q	0.6	0.4	

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- Defender's regret for playing "x" given payoff instance
  - Utility loss of defender to play x compared to optimal.

- defUtility(x) = -0.5
- defUtility(x*) = 0.2
- regret(x) = 0.7

Adversary

Defender

	Target 1	Target 2	x	$x^{*,l}$
Target 1	4, -4	-1, 1	0.3	0.7
Target 2	-5, 5	2, -2	0.7	0.3
q	0.6	0.4		
q^l	0.4	0.6		

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- Defender regret of "x" higher for another payoff instance
  - Max regret: Max over all payoff instances under uncertainty

- defUtility(x) = -0.9
- defUtility(x*) = 0.3
- regret(x) = 1.2

max_regret(x) = 1.2

Adversary

Defender

	Target 1	Target 2	x	$x^{*,2}$
Target 1	6, -6	-1, 1	0.3	0.8
Target 2	-4, 4	0, 0	0.7	0.2
q	0.8	0.2		
q^2	0.2	0.8		

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- Objective
  - Compute optimal defender strategy that minimizes max regret.

- Optimization

Infinite #regret constraints

$$\min_{x \in X,\, r \in R} r$$

$$\text{s.t. } r \geq \text{regret}(x, \text{payoff}), \forall \text{ payoff} \in I$$

Utility loss of playing x
given attacker follows SUQR

 Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

- ARROW: Incremental Payoff Generation

$$\min_{x \in X,\, r \in R} r$$

$$\text{s.t. } r \geq \text{regret}\left(x, \text{payoff}\right), \ \forall \ \text{payoff} \in I$$

Master:

- **Idea**: solve relaxed MMR with small sample set S of attacker payoffs, obtain **LB**

Slave:

- **Idea**: find new attacker payoff to add to the sample set, obtain **UB**

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

	x^1
Target 1	0.3
Target 2	0.7

Payoff 1

	Target 1	Target 2
Target 1	4, -4	-1, 1
Target 2	-5, 5	2, -2

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

	x^1	$x^{1,2}$
Target 1	**0.3**	**0.4**
Target 2	**0.7**	**0.6**

Payoff 1

	Target 1	Target 2
Target 1	**4, -4**	**-1, 1**
Target 2	**-5, 5**	**2, -2**

Payoff 2

	Target 1	Target 2
Target 1	**3, -3**	**0, 0**
Target 2	**-4, 4**	**1, -1**

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Game-theoretic Reasoning

	x^1	$x^{1,2}$	$x^{1,2,3}$	…
Target 1	0.3	0.4	0.6	…
Target 2	0.7	0.6	0.4	…

Payoff 1

	Target 1	Target 2
Target 1	4, -4	-1, 1
Target 2	-5, 5	2, -2

Payoff 2

	Target 1	Target 2
Target 1	3, -3	0, 0
Target 2	-4, 4	1, -1

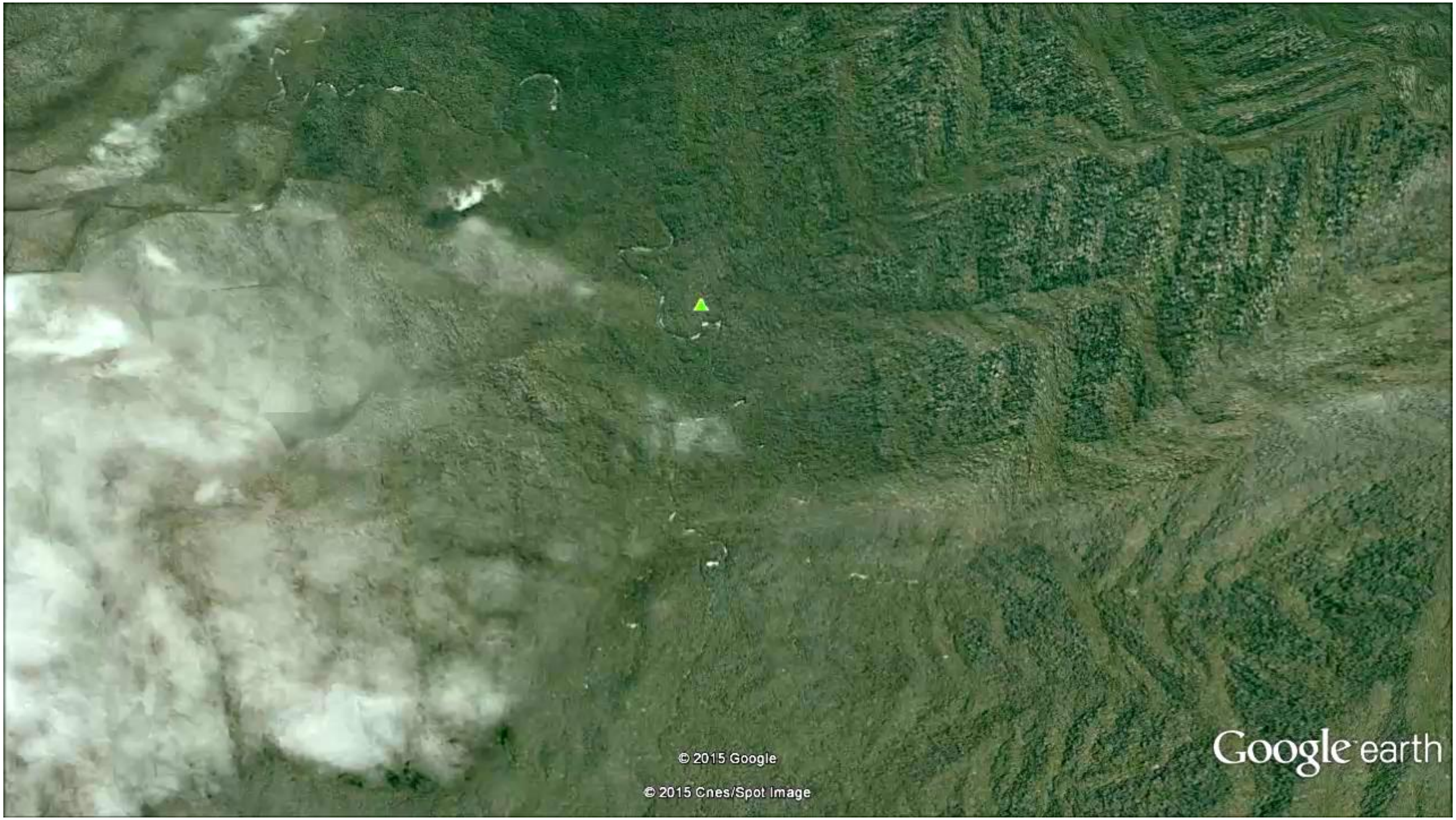
Payoff 3

	Target 1	Target 2
Target 1	5, -5	2, -2
Target 2	6, -6	0, 0

…

Nguyen et al. Making the most of our regrets: Regret-based solutions to handle payoff uncertainty and elicitation in green security games. In GameSec, 2015.

PAWS Component: Route Planning

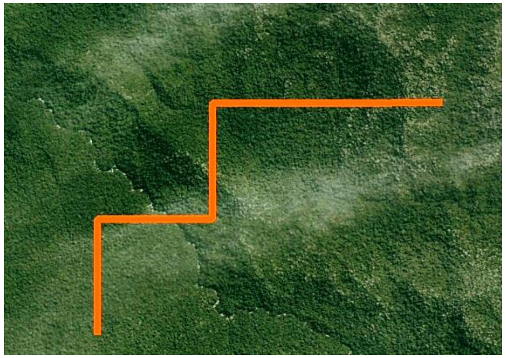


PAWS Component: Route Planning

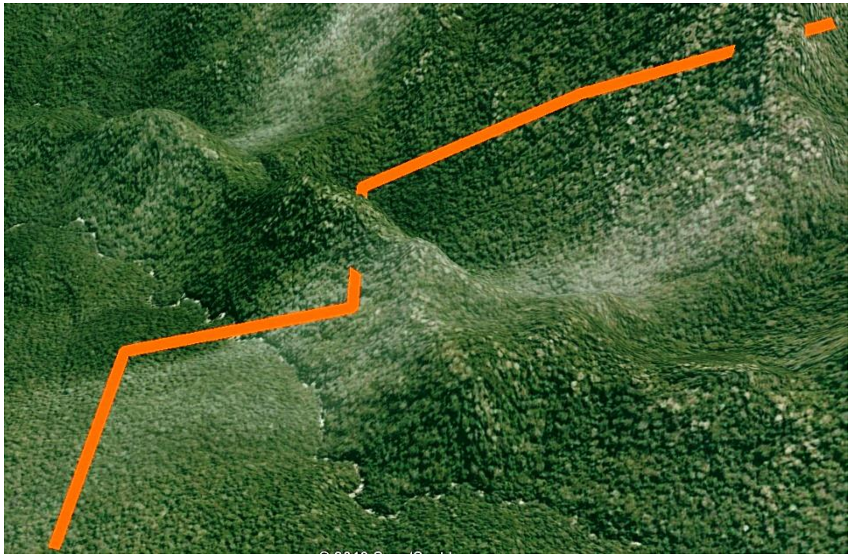
Defender Strategy

0.03	0.05	0.15
0.03	0.28	0.40
0.00	0.03	0.03

Patrol Route (2D)



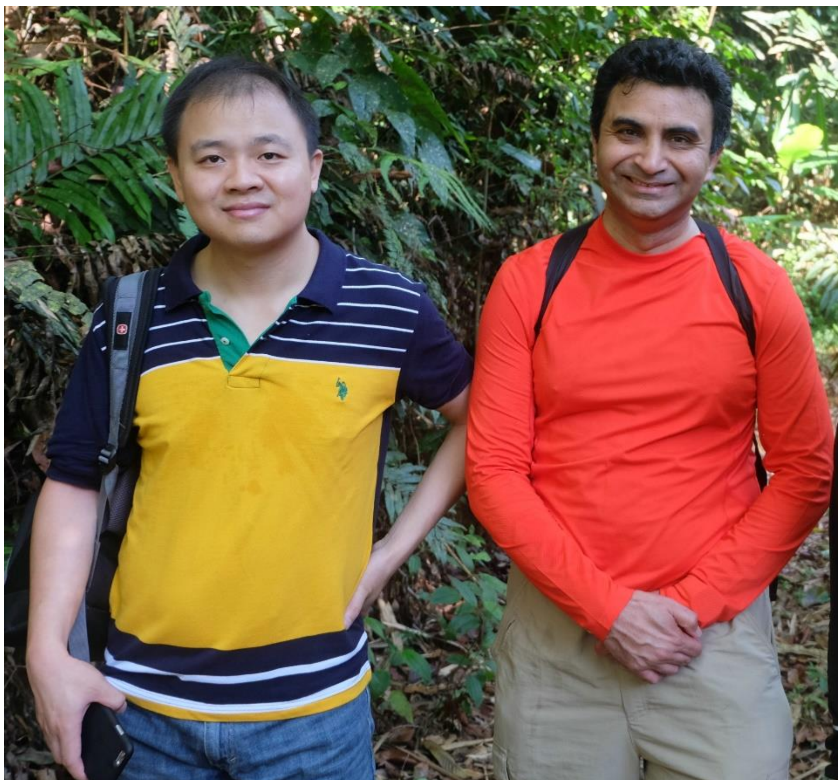
Patrol Route (3D)



Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Component: Route Planning

- 8-hour patrol in April 2015: patrolling is not easy!

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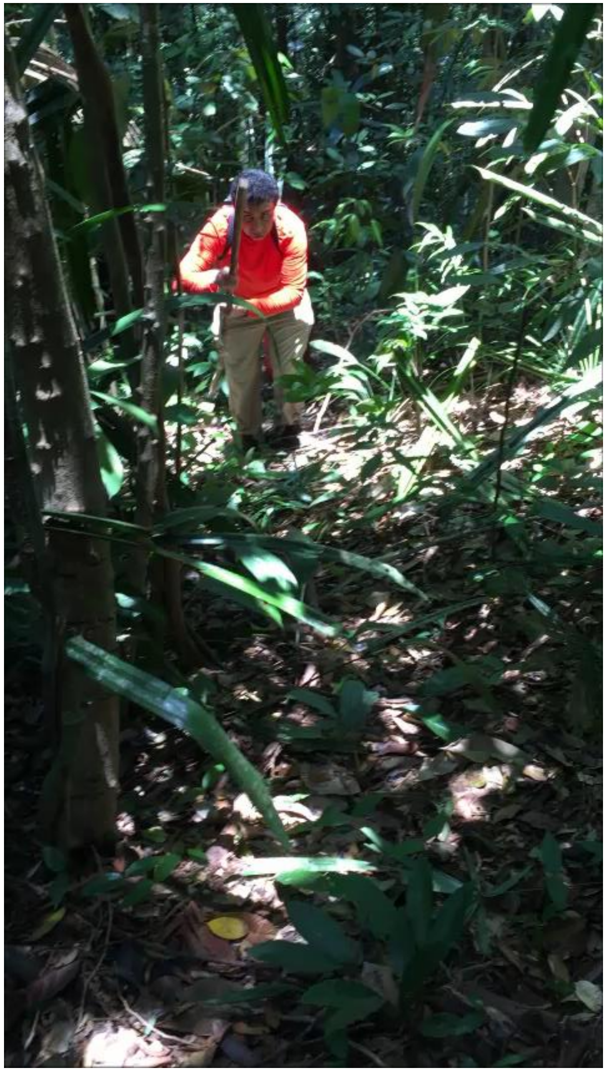
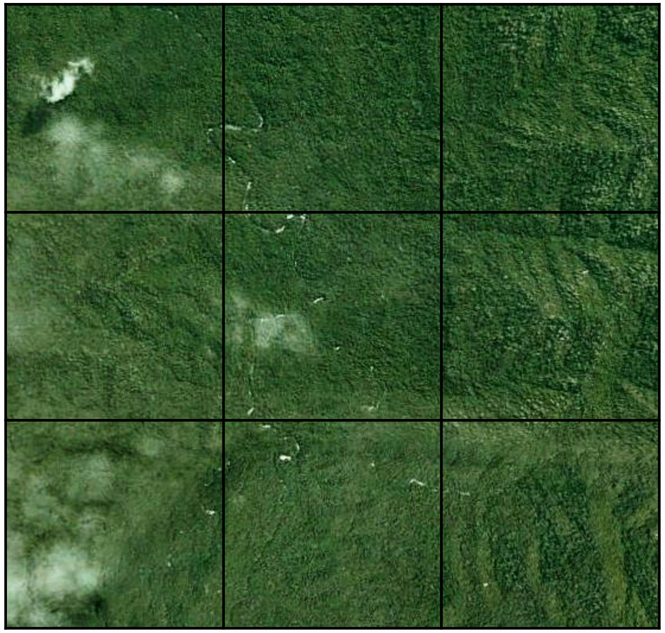
PAWS Component: Route Planning

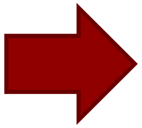


Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Component: Route Planning

- Grid based → Route based
- Hierarchical modeling: Focus on terrain features
- Build virtual street map





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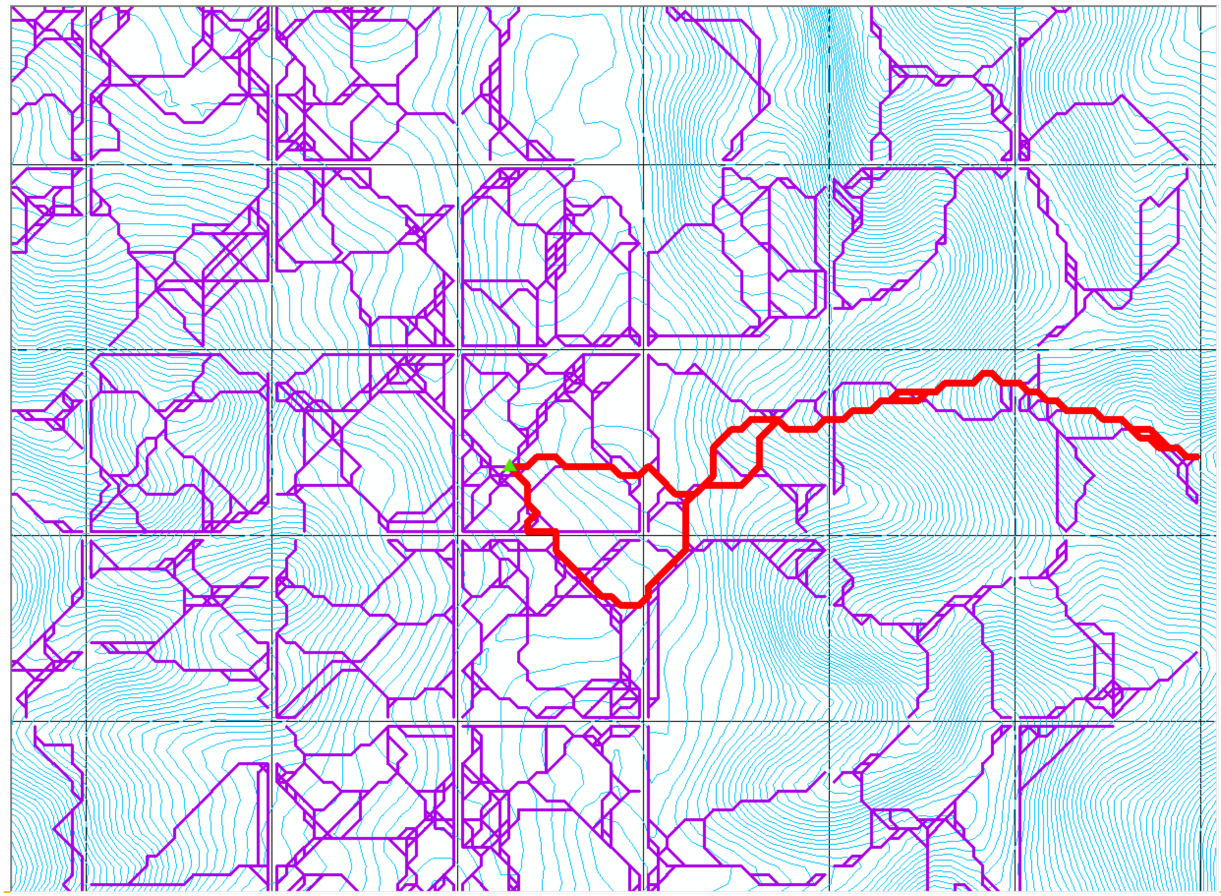
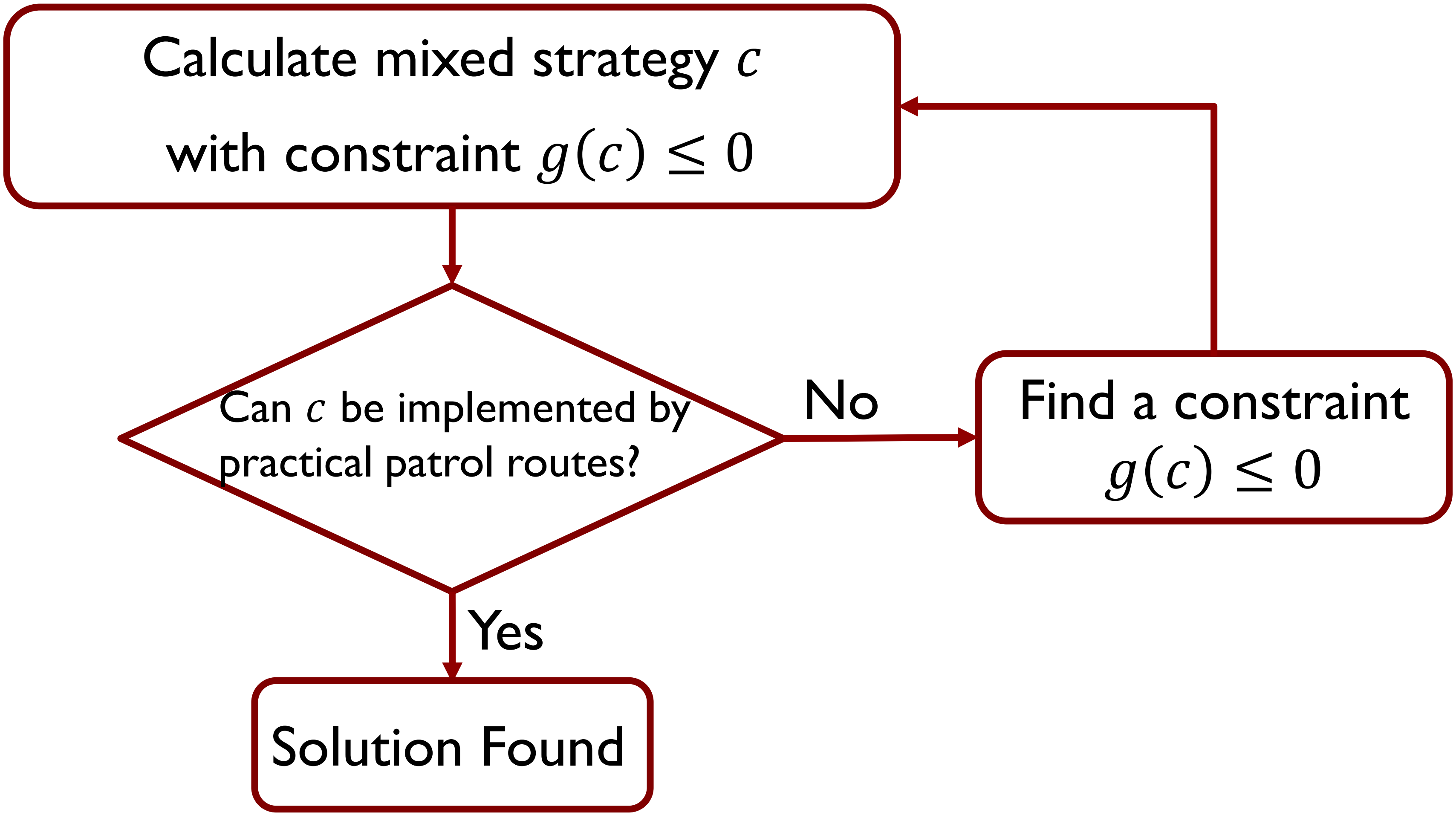
PAWS Component: Route Planning

- Hierarchical model: Focus on terrain feature



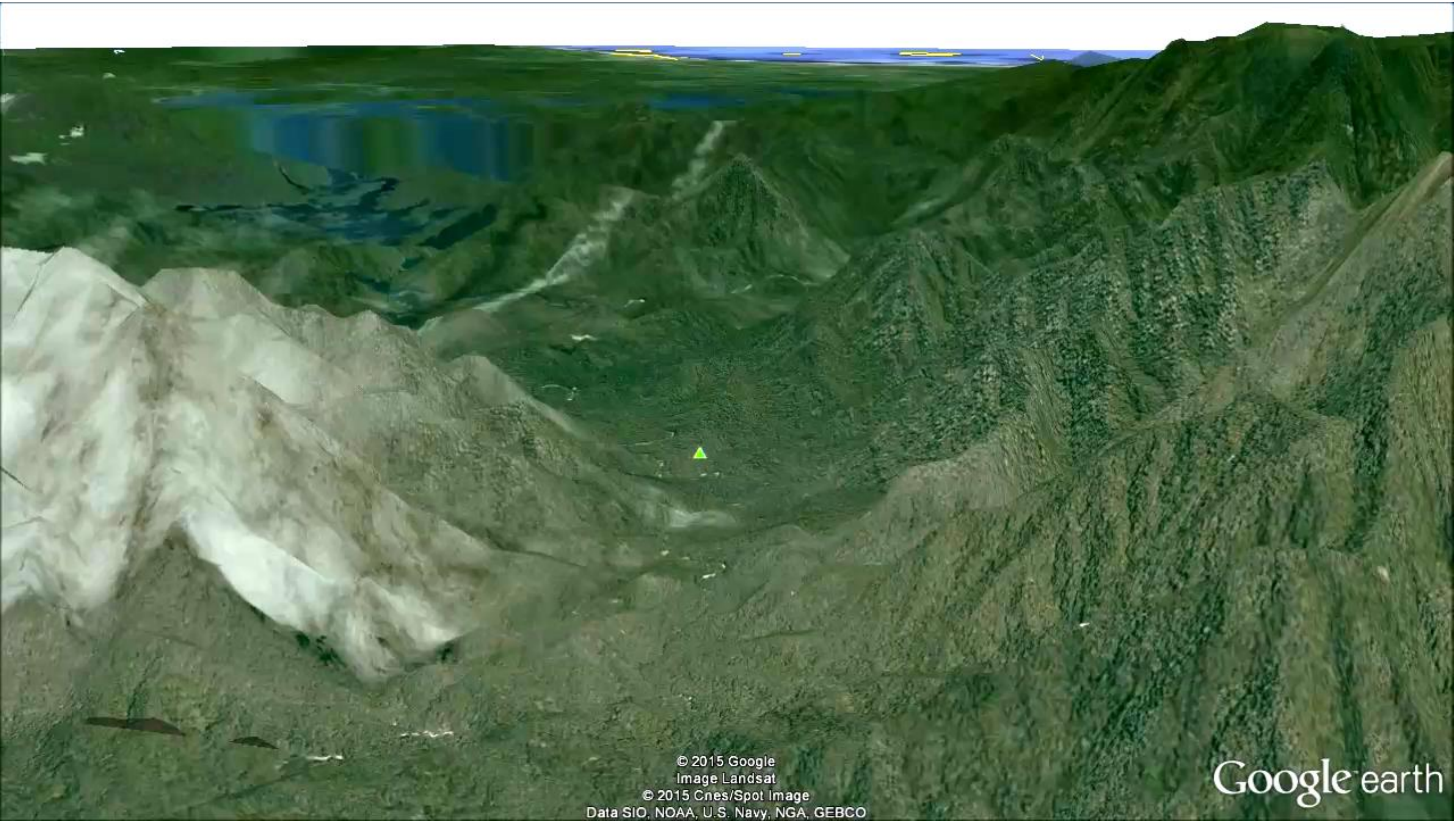
Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Component: Route Planning



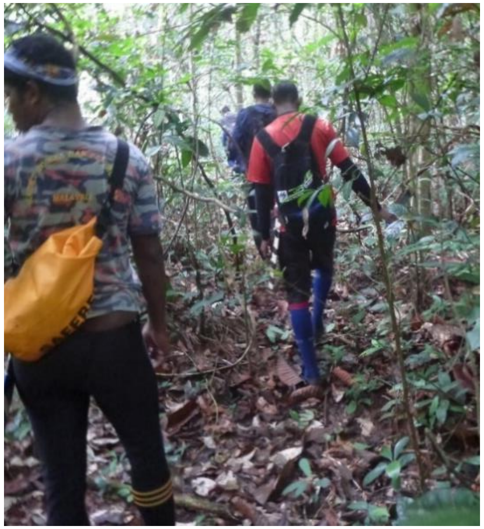
Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Component: Route Planning



PAWS Deployment

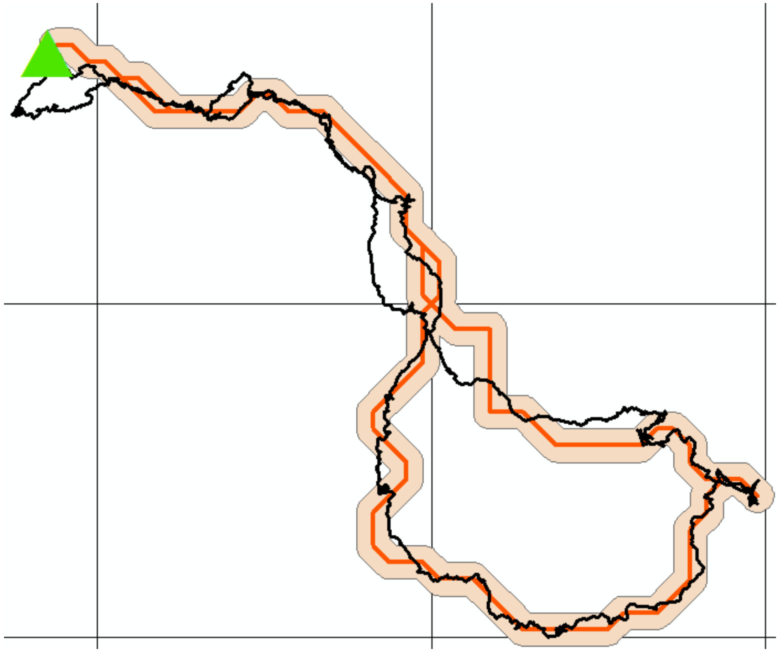
- In collaboration with Panthera, Rimba
- Regular deployment since July 2015 (Malaysia)


PAWS Deployment

Grid Based

Route Based



Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Deployment

Animal Footprint

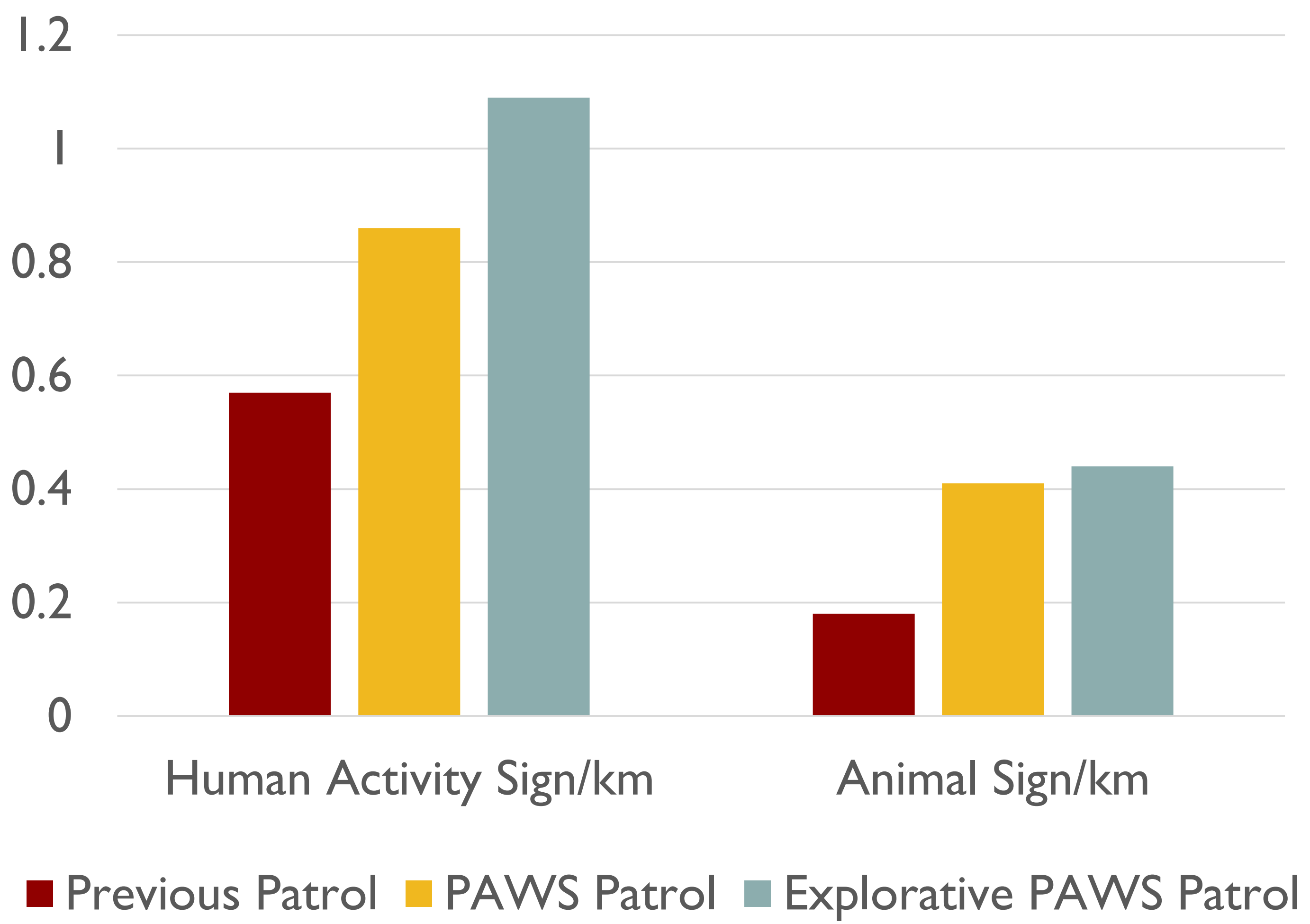
Tree Mark

Camping Sign

Tiger Sign

Lighter

PAWS Deployment



Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

PAWS Deployment

- PAWS is deployed in the field
  - Saved animals!

WCS

UGANDA WILDLIFE AUTHORITY

UWA

Conserving for Generations

Rimba

Because we NEED a jungle out there.

WWF

PANTHERA

LEADERS IN WILD CAT CONSERVATION

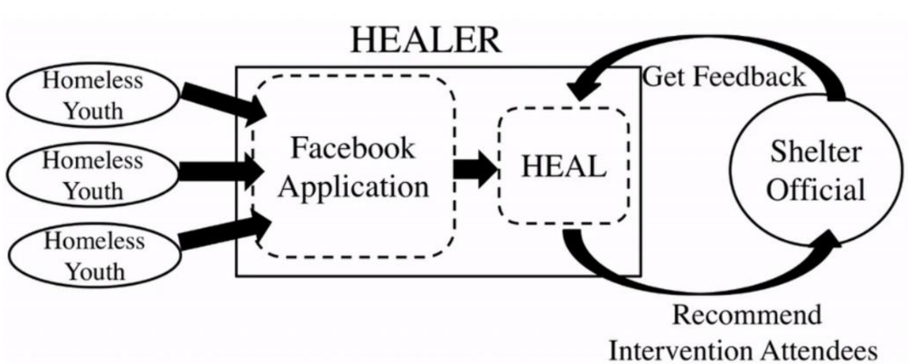
Fang et al. Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security. In IAAI, 2016.

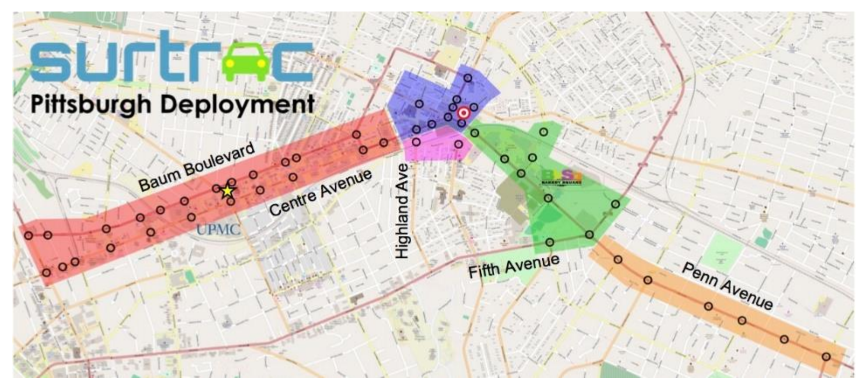
AI and Social Good

- AI research that can deliver societal benefits now and in the near future

http://mashable.com/2015/02/06/hiv-homeless-teens-algorithm/#..k9dRKhxaqm

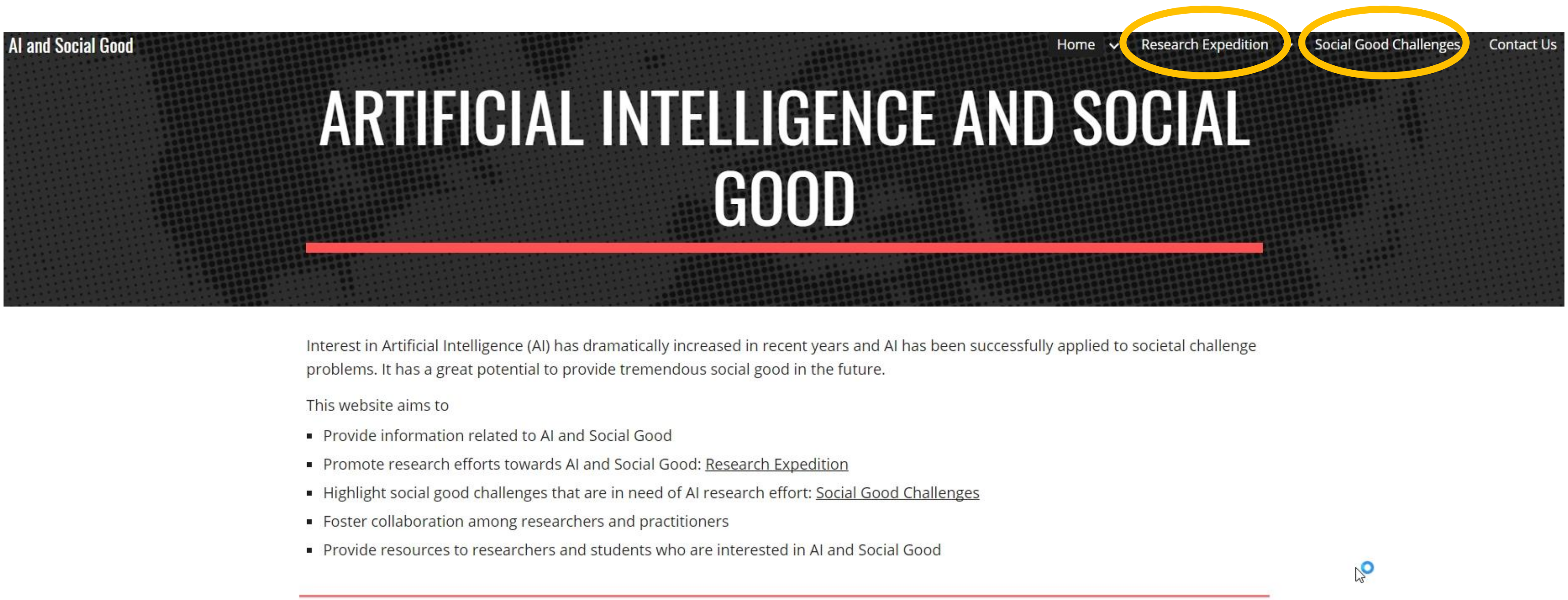
https://www.pastemagazine.com/articles/2017/04/a-new-smart-technology-will-help-cities-drasticall.html





AI and Social Good

- www.AIandSocialGood.org



THANK YOU!

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