Integrating Machine Learning with Game Theory for Societal Challenges

Fei Fang
Leonardo Assistant Professor
Carnegie Mellon University
feifang@cmu.edu

Security Challenges

Lack of Security Resources

Environmental Sustainability Challenges

Lack of Ranger/Conservation Resources

100 years ago ≈ 60,000 tigers

Today ≈ 3,200 tigers

Zero Hunger and Transportation Challenges

Inefficiencies in Crowd-based Platforms

Machine Learning + Game Theory for Societal Challenges

Security & Safety

Environmental Sustainability

Zero Hunger

Transportation

Artificial Intelligence

Computational Game Theory

Machine Learning

Societal Challenges

Machine Learning + Game Theory for Societal Challenges

Security & Safety

Environmental Sustainability

Zero Hunger

Transportation

AI has great potential for social good

There are many ways to integrate ML and GT

ARMOR for Airport Security [2007]

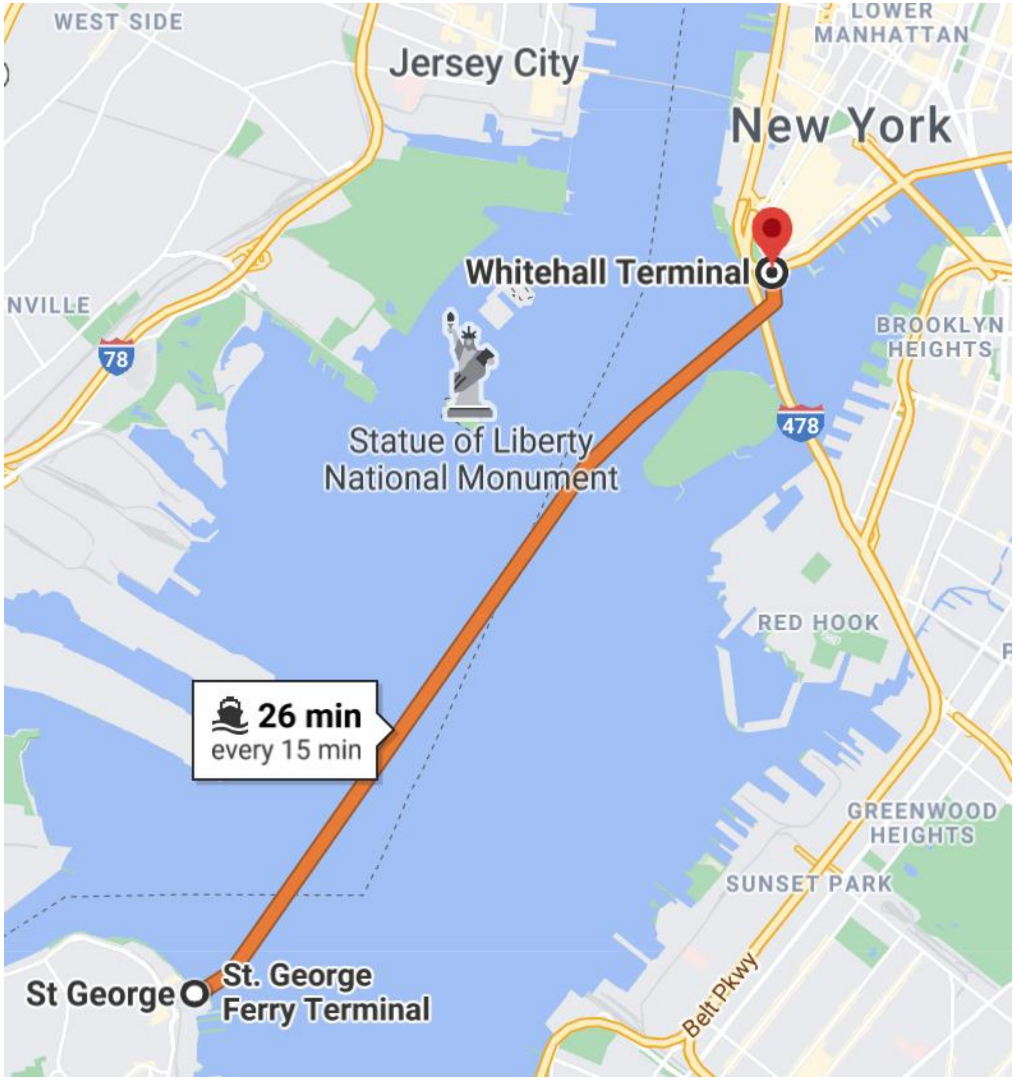
January 2009

- January 3rd — Loaded 9/mm pistol
- January 9th — 16-handguns, 1000 rounds of ammo
- January 10th — Two unloaded shotguns
- January 12th — Loaded 22/cal rifle
- January 17th — Loaded 9/mm pistol
- January 22nd — Unloaded 9/mm pistol

Pita, J., et al. Deployed armor protection: the application of a game theoretic model for security at the Los Angeles International Airport. In *AAMAS 2008*

Protecting Staten Island Ferry

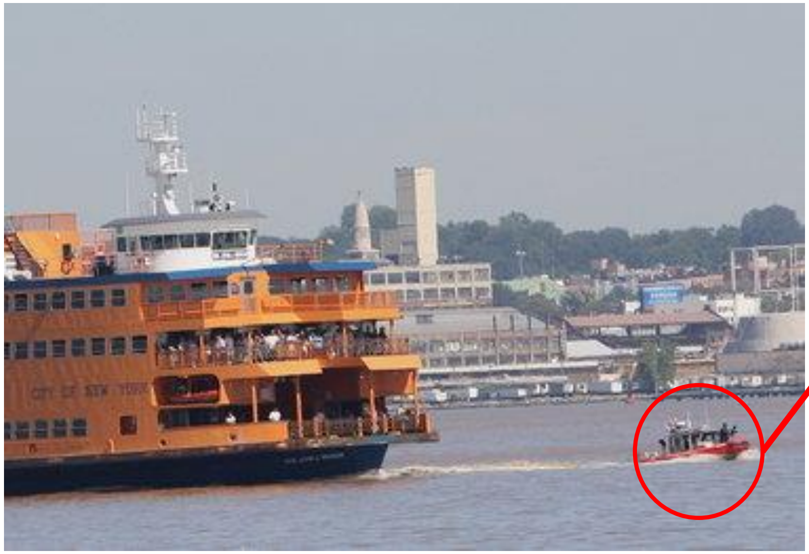
≈60,000 passengers a day on weekdays



Protecting Staten Island Ferry

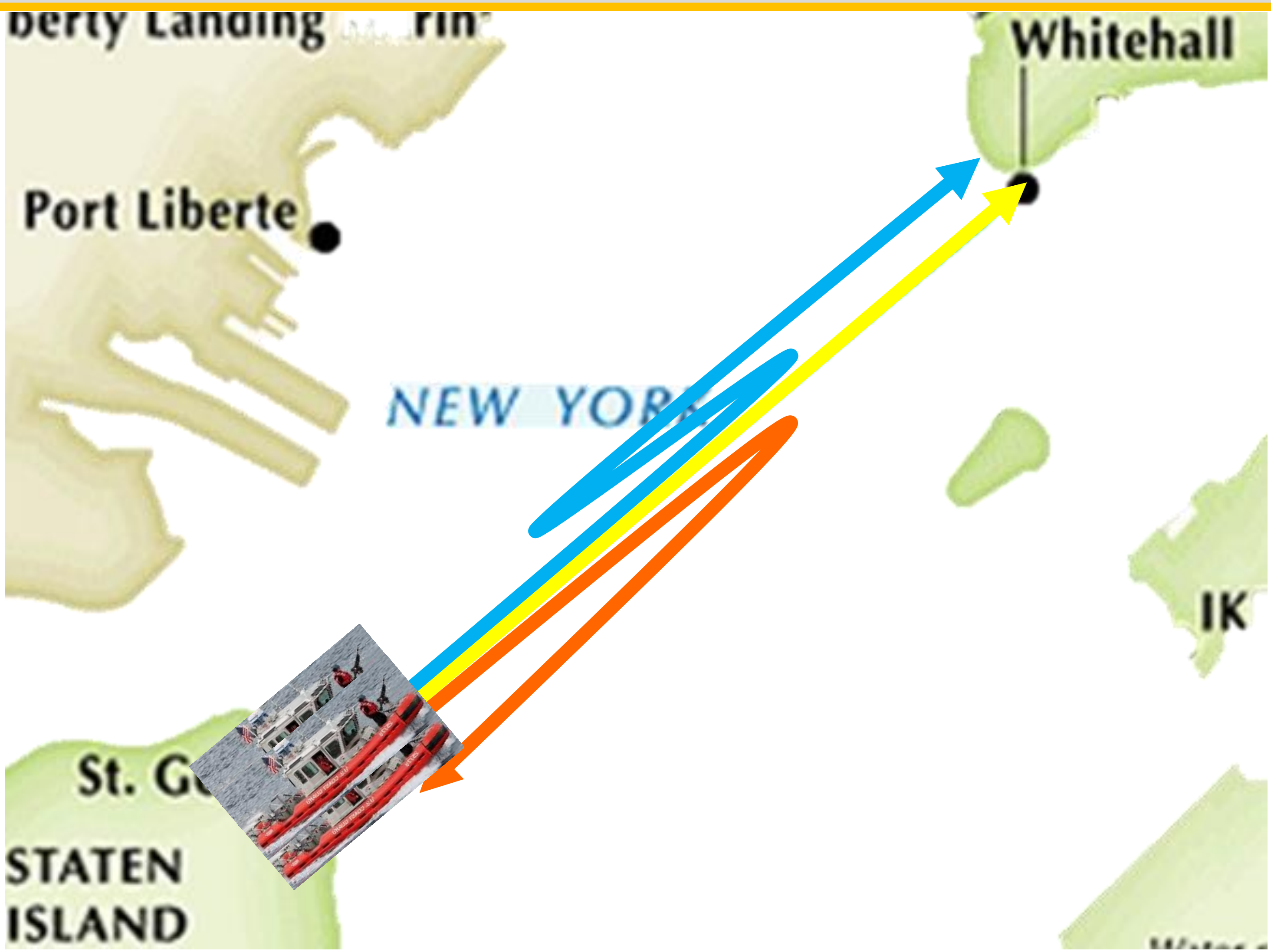
French supertanker Limburg 2002

USS Cole 2000



Previous USCG Approach

Problem: Find Optimal Patrol Strategy



Optimal Patrol Strategy for Protecting Moving Targets with Multiple Mobile Resources
Fei Fang, Albert Xin Jiang, Milind Tambe. In AAMAS-13: The Twelfth International Conference on Autonomous Agents and Multiagent Systems, May 2013

Proposed Solution: Game-Theoretic Model

- Model defender-attacker behavior using Stackelberg security game
- Attacker's payoff: $u_i(t)$ if not protected, 0 otherwise
- Minimax – minimize maximum attacker's expected utility

$$\min_{p_r} \max_{i,t} u_i(t) \times \mathbb{P}[\text{target not protected}]$$

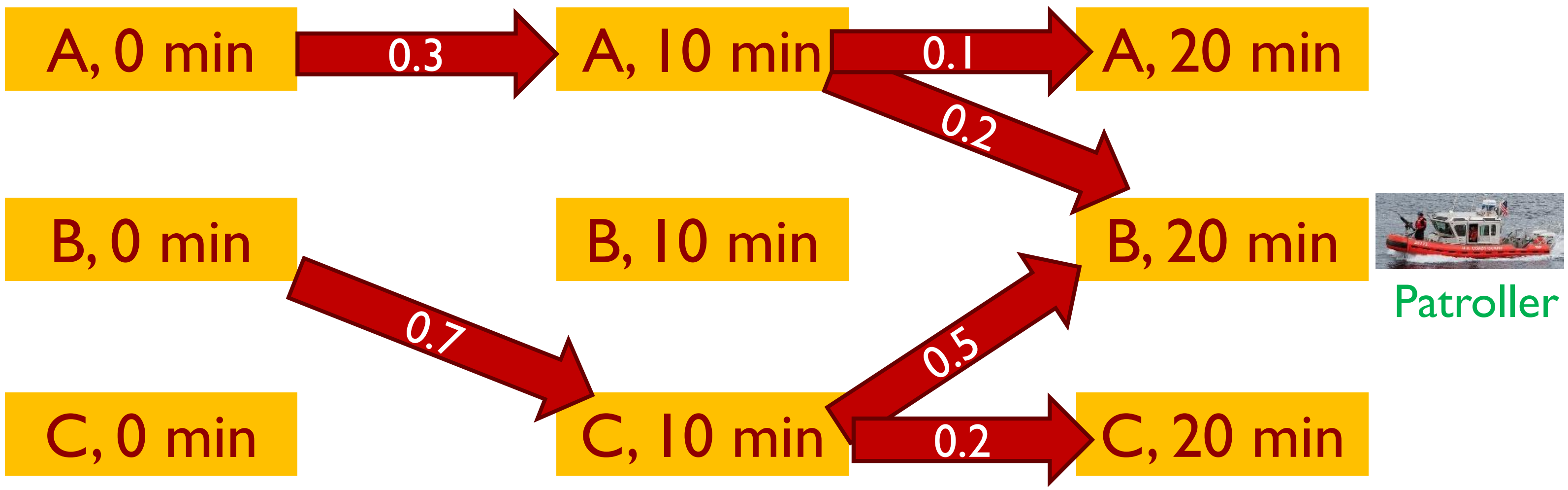
- Key technical challenge: infinite actions

Adversary

Defender p_r		10:00:00 AM Target 1	10:00:01 AM Target 1	…	10:30:00 AM Target 3	…
30%	Purple Route	-5, 5	-4, 4		0, 0	
40%	Orange Route					
20%	Blue Route					
	……					

Proposed Solution: Linear Programming

- Graph-based representation + Critical time points



$$\min_{\boxed{f}} v$$

Prob. flow over feasible edges

$$\text{s.t. } \sum_{e \in (i,t)\rightarrow} f(e) = \sum_{e \in \rightarrow(i,t)} f(e)$$

$$\sum_{e \in (*,t)\rightarrow} f(e) = 1$$

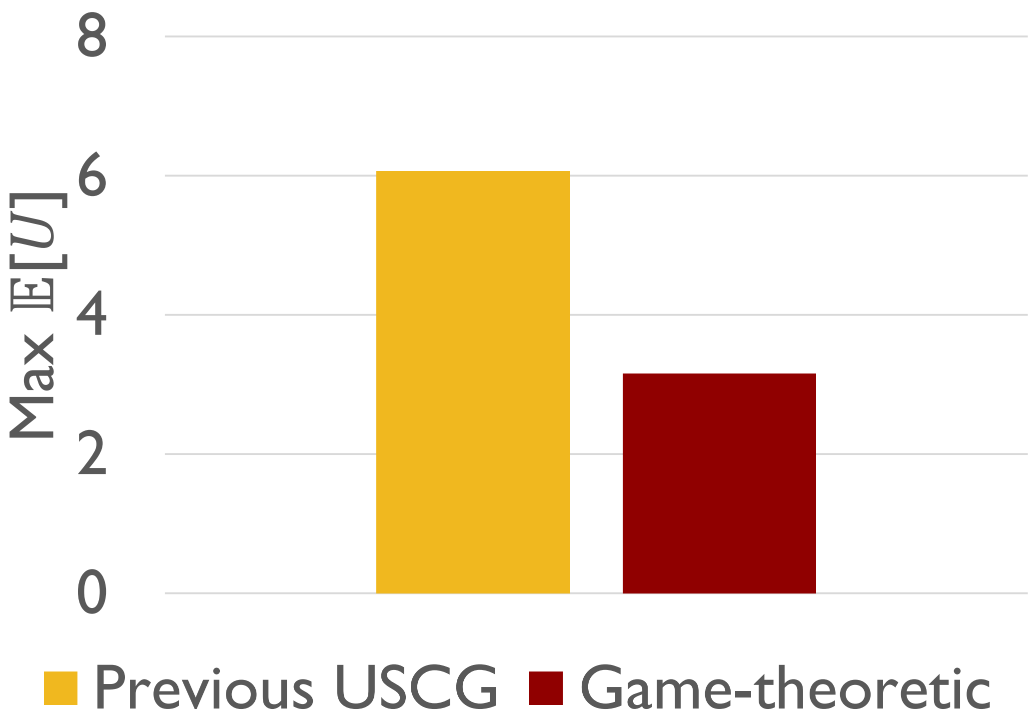
f is a unit flow

$$v \geq u_i(t) \times \mathbb{P}[\text{target not protected}], \forall i, \ \forall t \in \{t^*\}$$

Best response

Evaluation: In-Lab Simulation

Reduce potential risk by 50%



Real-World Deployment: Improved Patrol Efficiency

With US Coast Guard

Real-World Feedback

- USCG evaluation
  - Point defense to zone defense
  - Increased randomness
- Professional mariners
  - Apparent increase in Coast Guard patrols
- $33m dollar saving in 10 years[1]
- Continue to impact the policy

1. Von Winterfeldt, et al, 2020. Assessing the Benefits and Costs of Homeland Security Research: A Risk-Informed Methodology with Applications for the US Coast Guard. *Risk analysis*, *40*(3), pp.450-475.

Real-World Feedback: Improved Perceived Safety

3 of 5

107	0	66
VIEWS	COMMENTS	SHARES

About this iReport

- Not verified by CNN

Posted September 8, 2013 by **shortysmom**

U.S. Coast Guard protects the Staten Island Ferry: I feel safe!

By shortysmom | Posted September 8, 2013 | Staten Island, New York

Recognition

COMMANDER, ATLANTIC AREA
UNITED STATES COAST GUARD
431 CRAWFORD STREET
PORTSMOUTH, VIRGINIA 23704-5004

April 04, 2013

Dear Ms. Fang,

On behalf of the Atlantic Area Command, I wish to
enthusiasm and support shown by members of the Unive
Center for Risk and Economic Analysis of Terrorism Ev
development and implementation of the Port Resilience
Combat Terrorism (PROTECT) Model.

Summary: AI for Security

- Our work
  - First work dealing with continuous time and space in security games
  - Deployed by US coast guard and continue to impact their patrol policy

- Open questions
  - Coordinate multiple teams of security resources in complex spatio-temporal environments
  - Account for multiple threat models simultaneously [Chen et al., 2021; Milani et al., 2020; Shi et al., 2020]

Machine Learning + Game Theory for Societal Challenges

Security & Safety

Environmental Sustainability

Zero Hunger

Transportation

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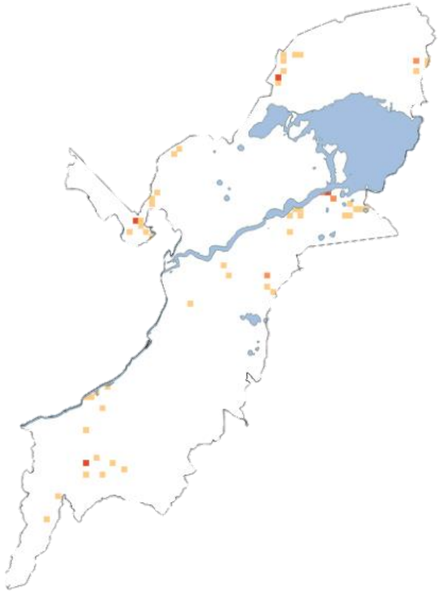
Machine Learning

Societal Challenges

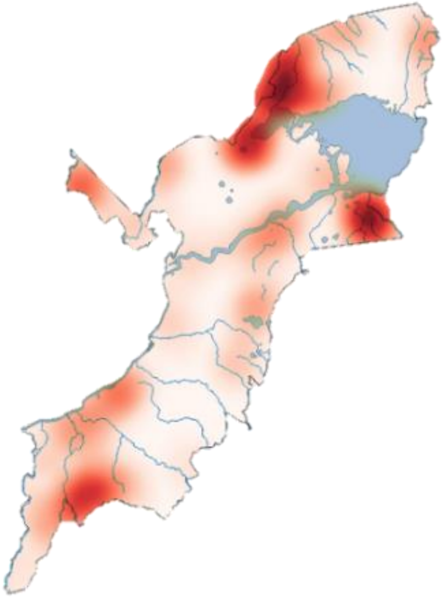
How to better protect wildlife using AI?

Learn Poacher Behavior from Real-World Data

12yr of poaching data from Queen Elizabeth National Park in Uganda

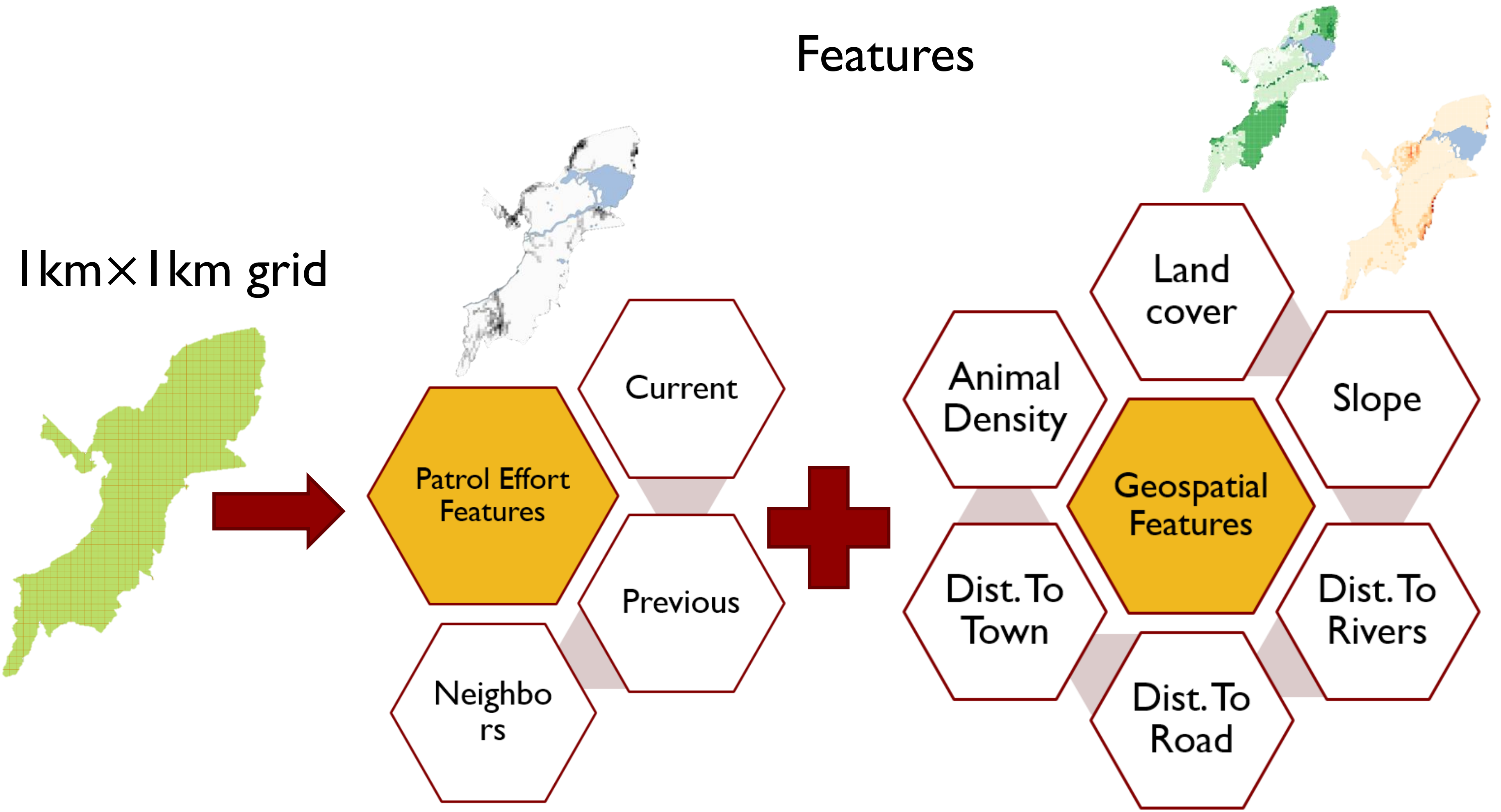


Prob. of snaring or Prob. of detection



With Uganda Wildlife Authority and Wildlife Conservation Society

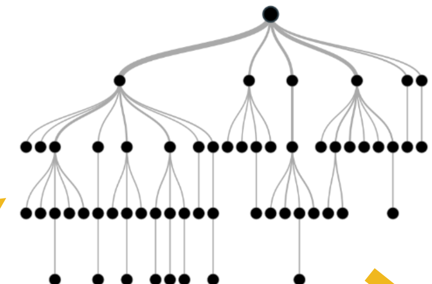
Learn Poacher Behavior from Real-World Data

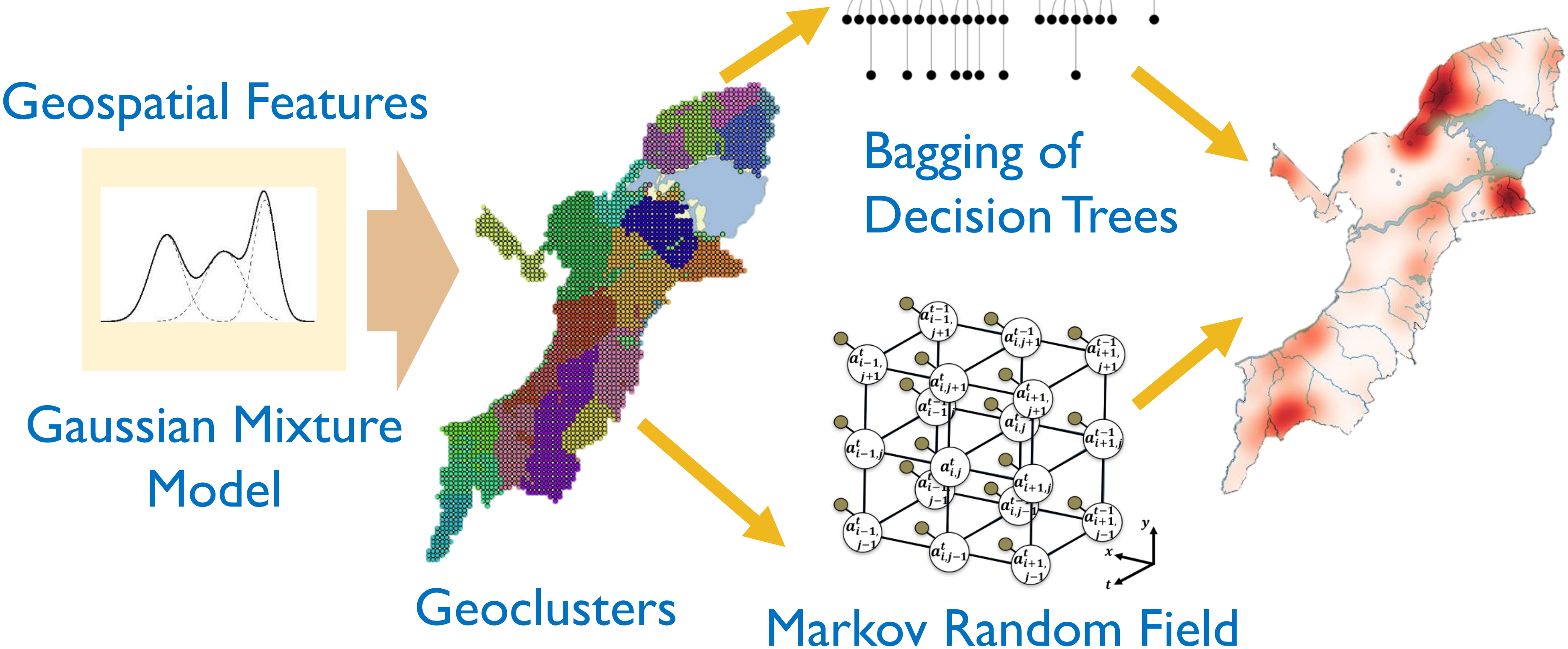


With Uganda Wildlife Authority and Wildlife Conservation Society

Learn Poacher Behavior from Real-World Data

- Key technical challenges
  - Lack of labeled data
  - Data imbalance



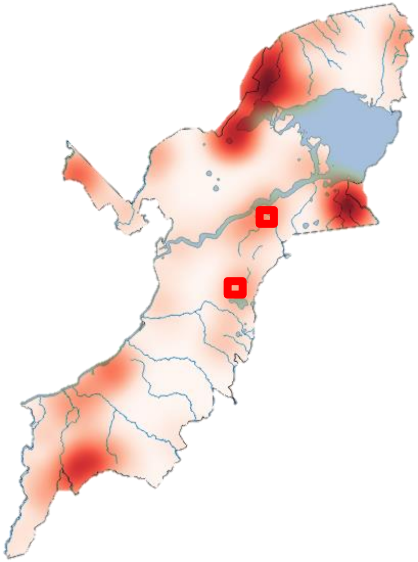


Taking it for a Test Drive: A Hybrid Spatio-temporal Model for Wildlife Poaching Prediction Evaluated through a Controlled Field Test. Shahrzad Gholami, Benjamin Ford, Fei Fang, Andrew Plumptre, Milind Tambe, Margaret Driciru, Fred Wanyama, Aggrey Rwetsiba, Mustapha Nsubaga, Joshua Mabonga. In ECML-PKDD 2017

1 Month Field Test in Uganda

- Findings
  - 19 litter, ashes, etc.
  - 1 poached elephant
  - 1 active snare
  - 10 antelope snares
  - 1 roll of elephant snares

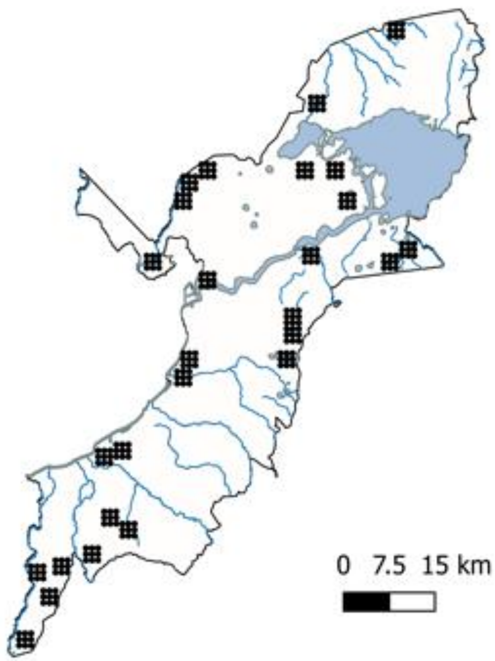


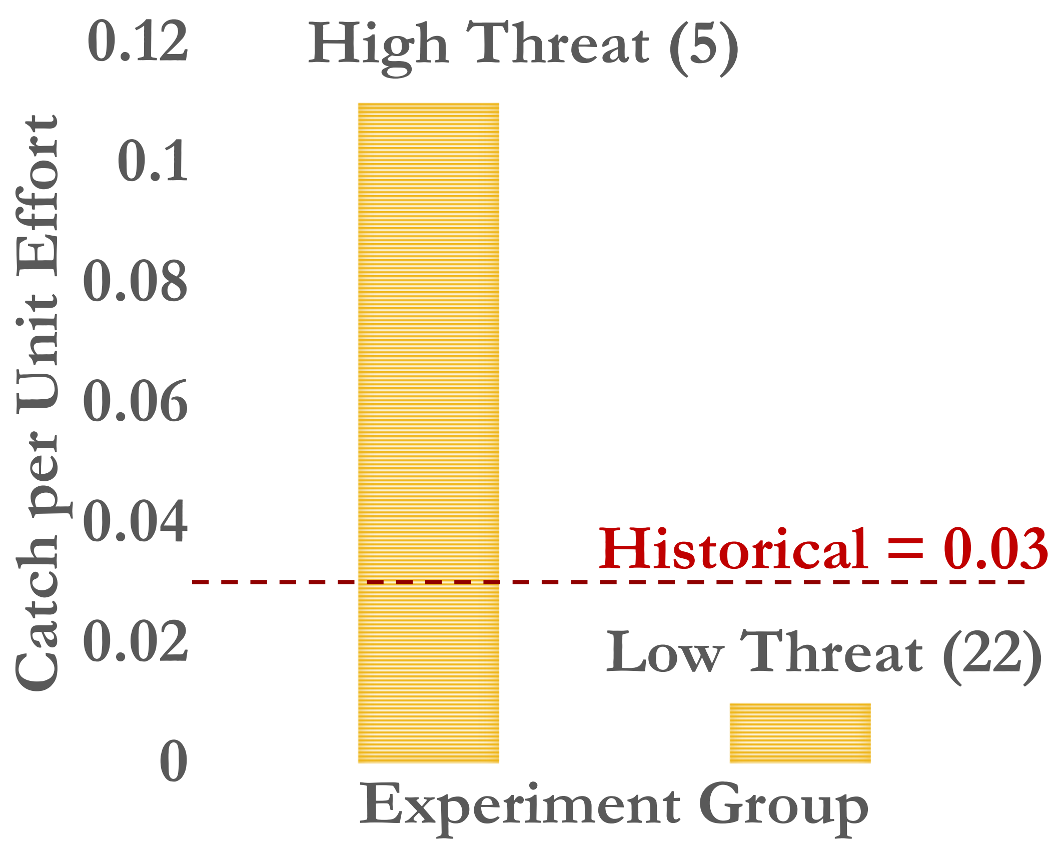
Historical Base Hit Rate	Our Hit Rate
Average: 0.73	3 (>91% months)

Kar, D., Ford, B., Gholami, S., Fang, F., Plumptre, A., Tambe, M., Driciru, M., Wanyama, F., Rwetsiba, A., Nsubaga, M. and Mabonga, J., 2017. Cloudy with a chance of poaching: Adversary behavior modeling and forecasting with real-world poaching data.

8 Month Field Test in Uganda



- 27 areas
- 452 km patrolled
- Can differentiate H/L threat areas



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Improving the Learning Framework

- Extract geospatial feature from satellite imagery
- Exploit human experts' knowledge

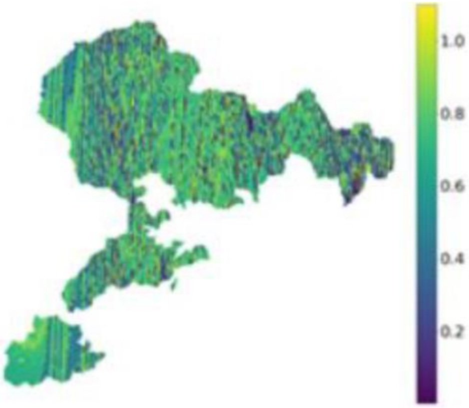
Data from patrols and satellite imagery

Questionnaire for Rangers

Machine Learning Methods

Ensemble Learning, Decision Trees, Neural Networks, Gaussian Process, Markov Random Field, …

Predicted poaching threat



With the World Wide Fund for Nature and Huang Ni He Forest Bureau

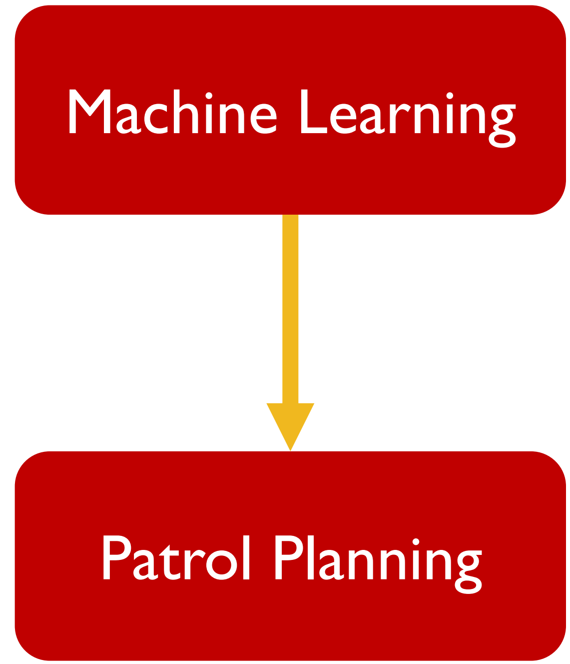
Field Tests in China

- 2-day field test in 2017: 22 snares
- 2017 winter season: 34 patrol shifts, 7 snares
- 1-week field test in 2019: 42 snares, 3 encounters



Gurumurthy et al. Exploiting Data and Human Knowledge for Predicting Wildlife Poaching. In COMPASS-18; Chen, W., et al, 2021. Data-Driven Multimodal Patrol Planning for Anti-poaching. In *Proceedings of the AAAI Conference on Artificial Intelligence.*

Patrol Planning Based on Learned Poacher Model

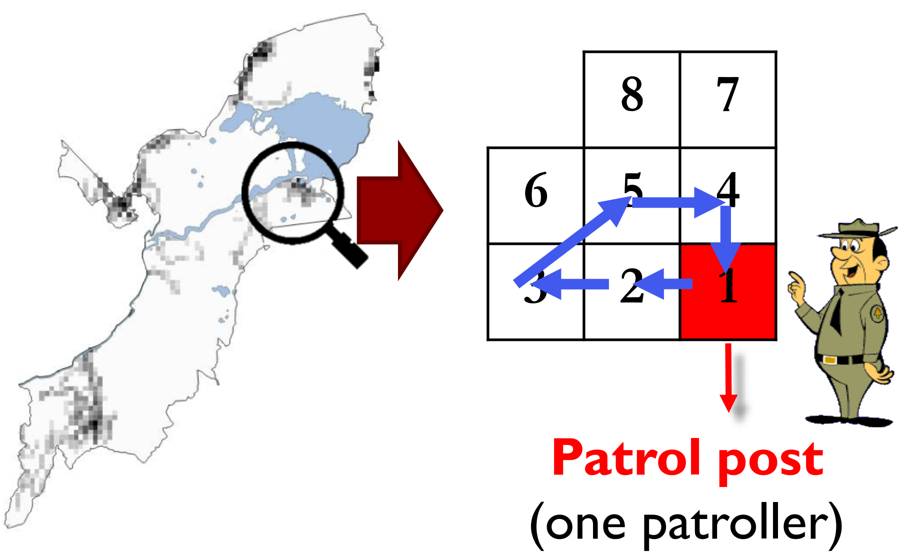


Patrol Planning Based on Learned Poacher Model

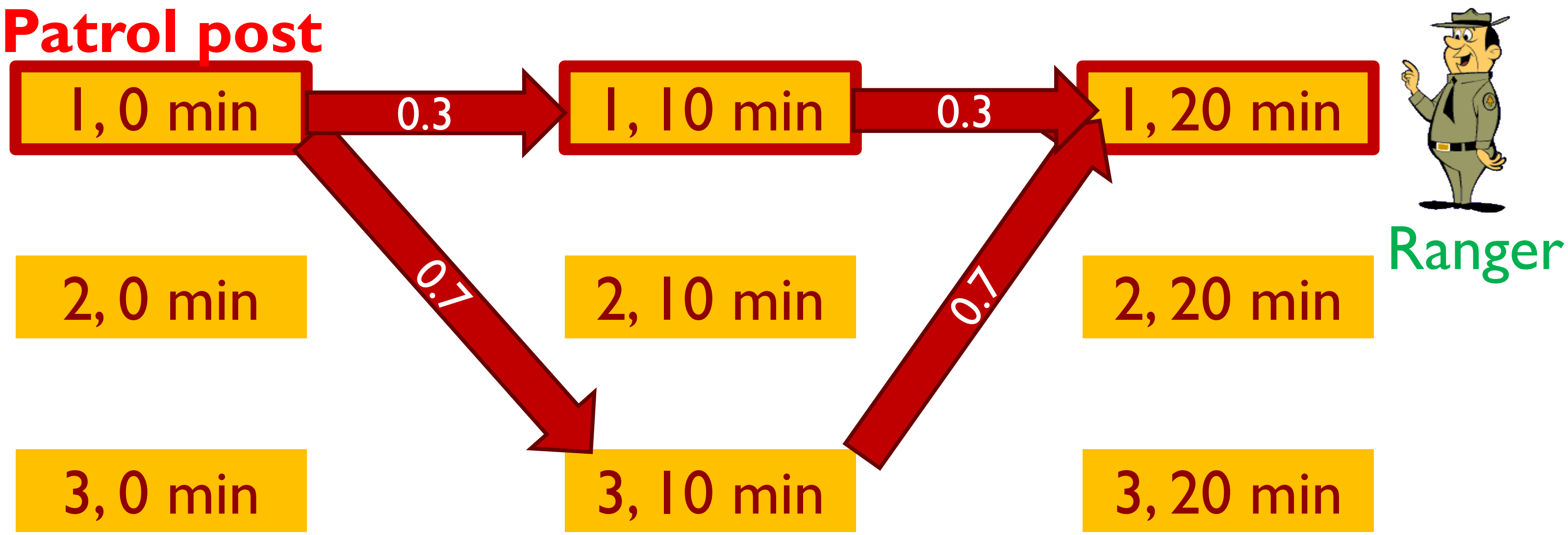
Learned Behavior Model

$\boldsymbol{x}$: Current patrol effort vector → g → $\boldsymbol{y}$: Probabilities of snaring or detection

- $\max_{x_i} \sum_i y_i$
- Scheduling constraint



Patrol Planning Based on Learned Poacher Model



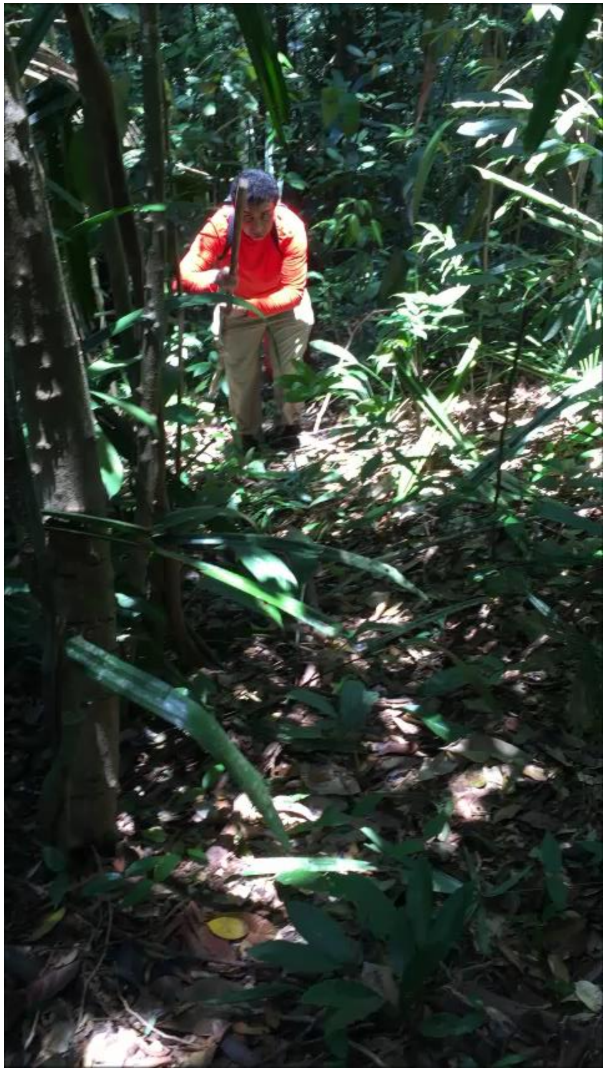
$$\max_{x_i} \sum_i y_i$$

s.t. $x_i = \sum_t \sum_{e \in (i,t)\rightarrow} f(e)$

f is a unit flow

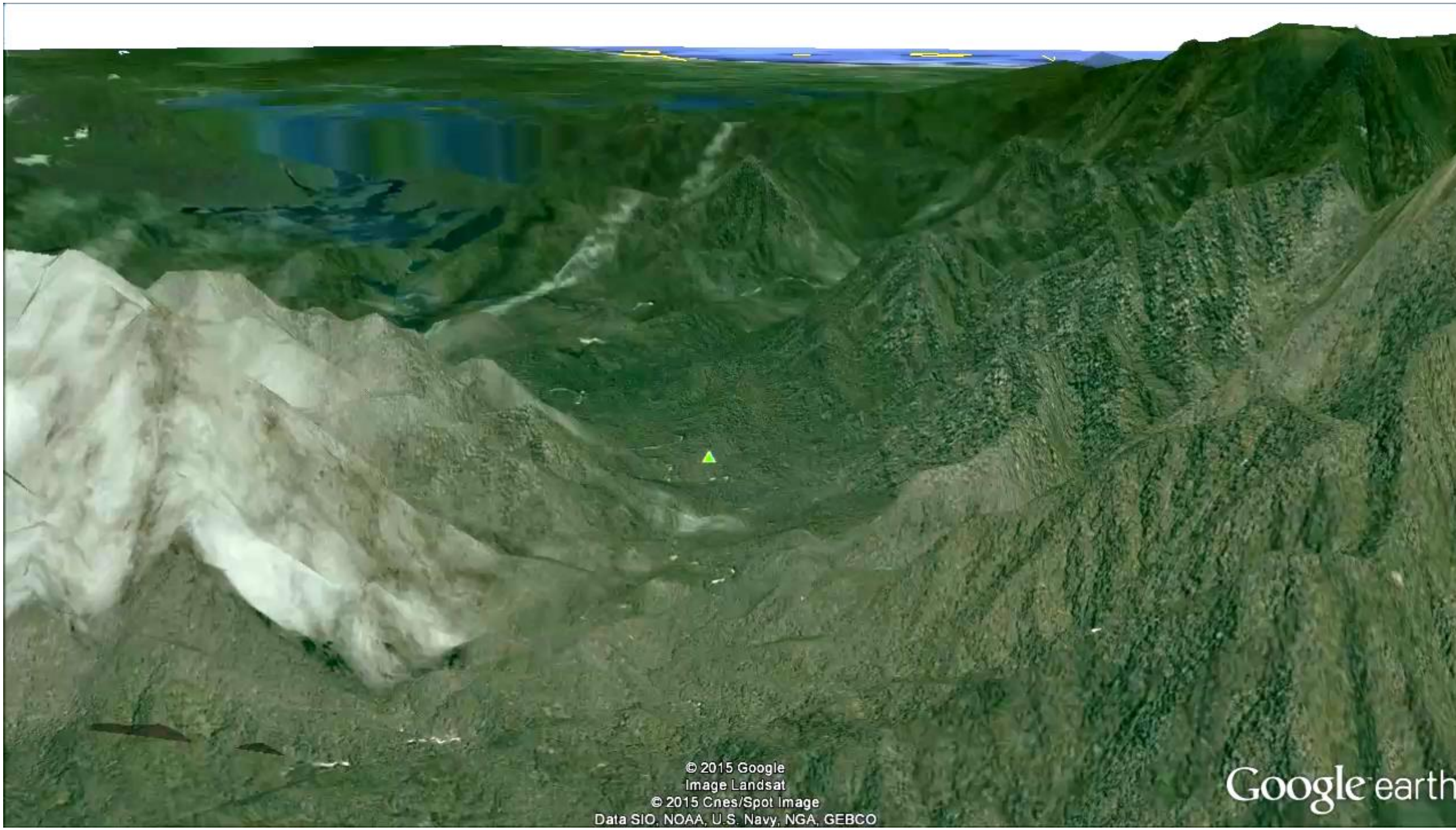
Xu, H., et al. 2017. Optimal patrol planning for green security games with black-box attackers. In International Conference on Decision and Game Theory for Security (pp. 458-477). Springer, Cham.

Complex Terrain



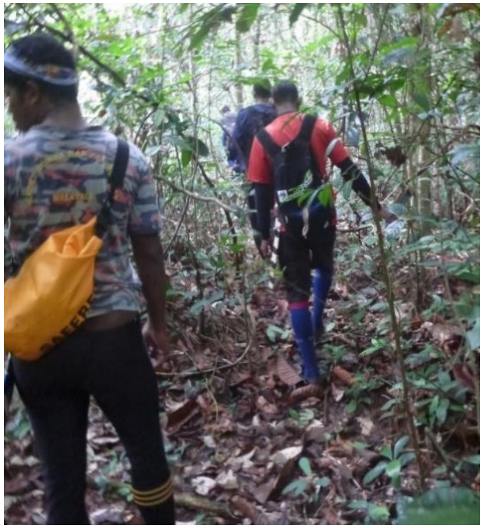
With Panthera and Rimba

Incorporate Terrain Info in Patrol Planning



Deploying PAWS: Field Optimization of the Protection Assistant for Wildlife Security
Fei Fang, Thanh H. Nguyen, Rob Pickles, Wai Y. Lam, Gopalasamy R. Clements, Bo An, Amandeep Singh, Milind Tambe, Andrew Lemieux
In IAAI-16: The Twenty-Eighth Annual Conference on Innovative Applications of Artificial Intelligence, February 2016

Field Test in Malaysia

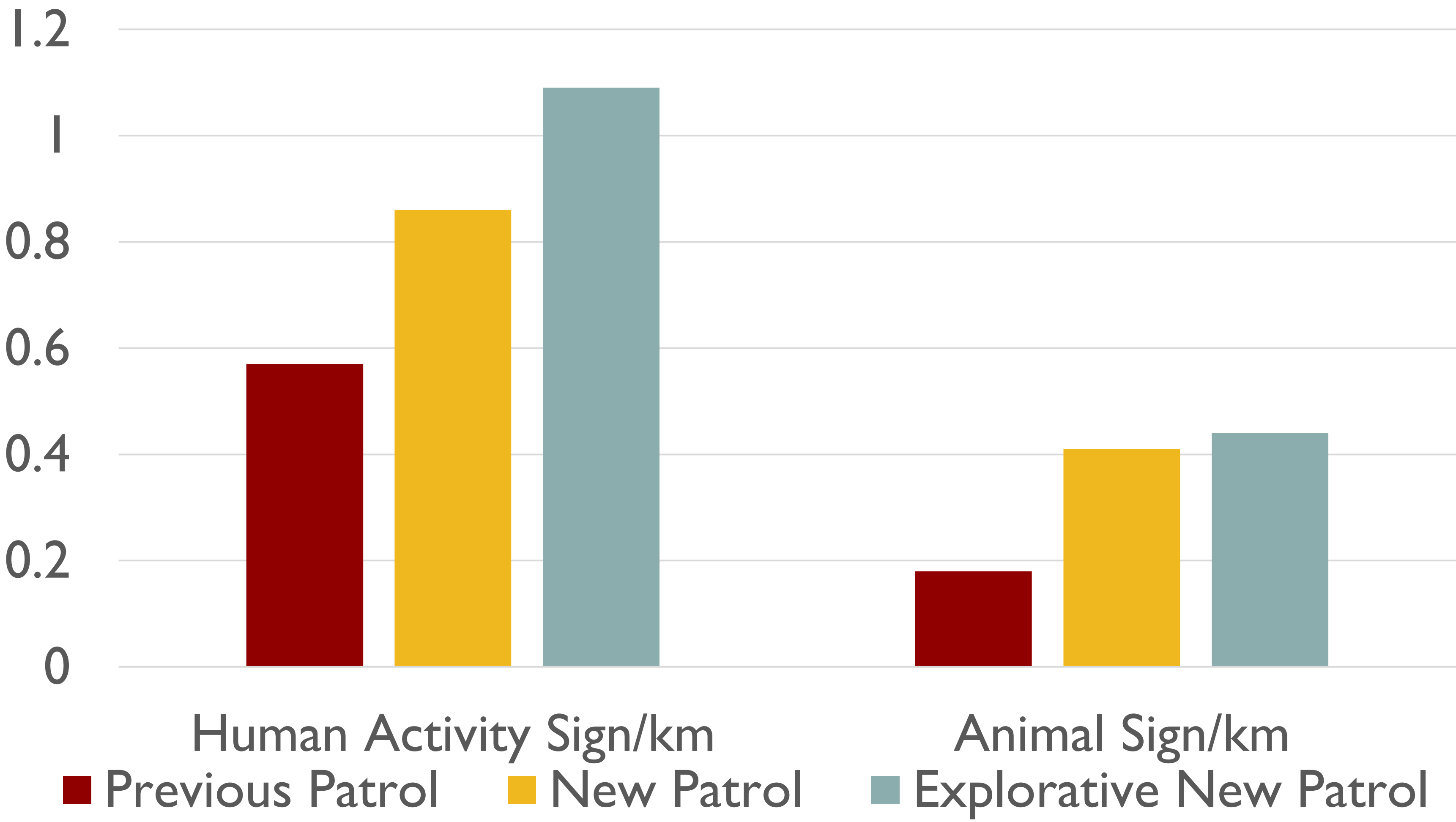


Animal Footprint

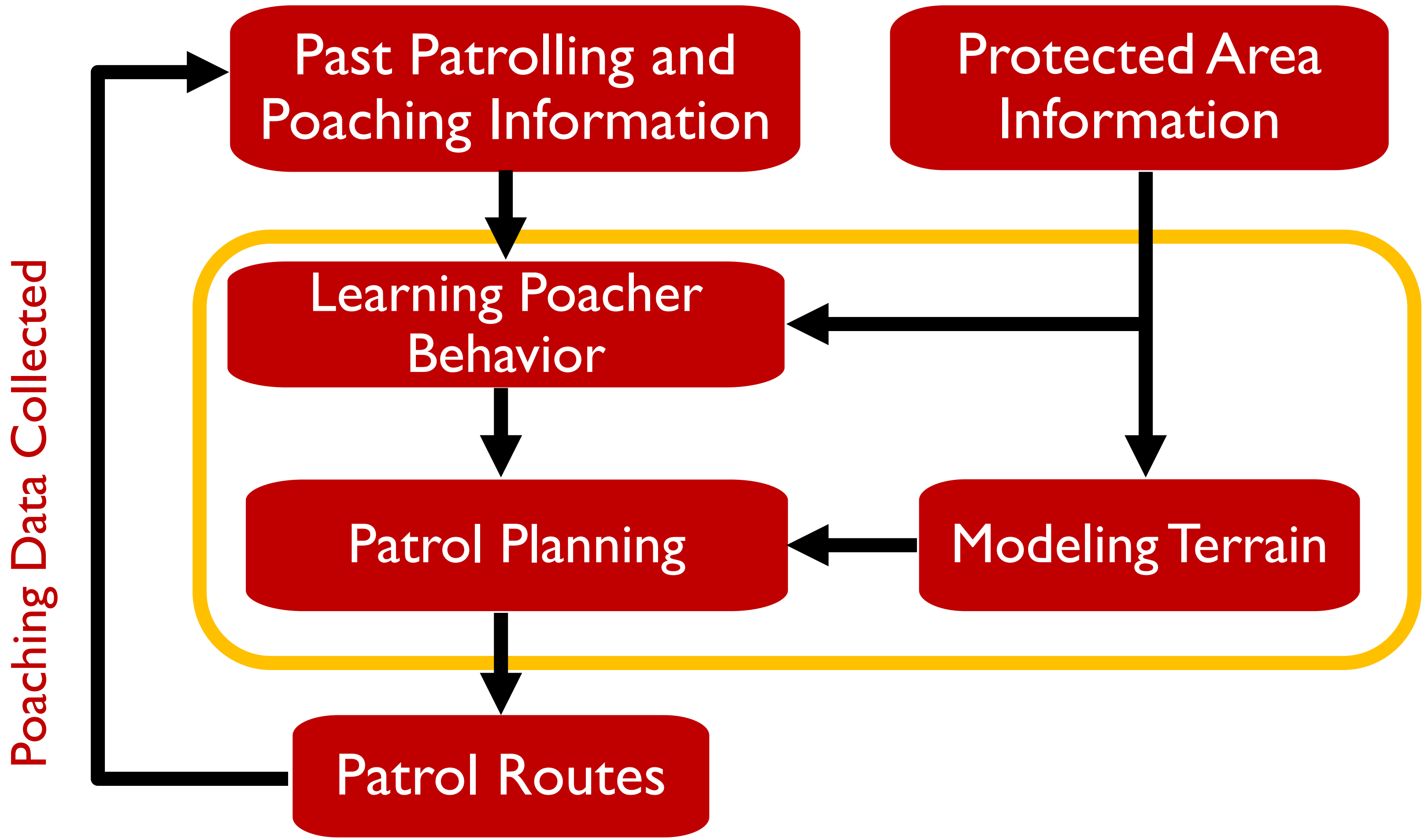
Tiger Sign

Lighter

Field Test in Malaysia



PAWS: Protection Assistant for Wildlife Security



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PAWS Now Available to Sites World Wide

- Successfully integrated into SMART
- Available to more than 600 sites worldwide
- Already in use in some parks (e.g., Cambodia)
- More field tests on the way

New Research Challenges Arise

- Patrol with real-time information
- UAV & human coordinated patrols
- Community engagement
- Zoning & Fine policy design

New Challenge: Patrol with Real-Time Information

- Rangers and poachers react to real-time information

- Model the sequential interaction as a Markov game

Footprints

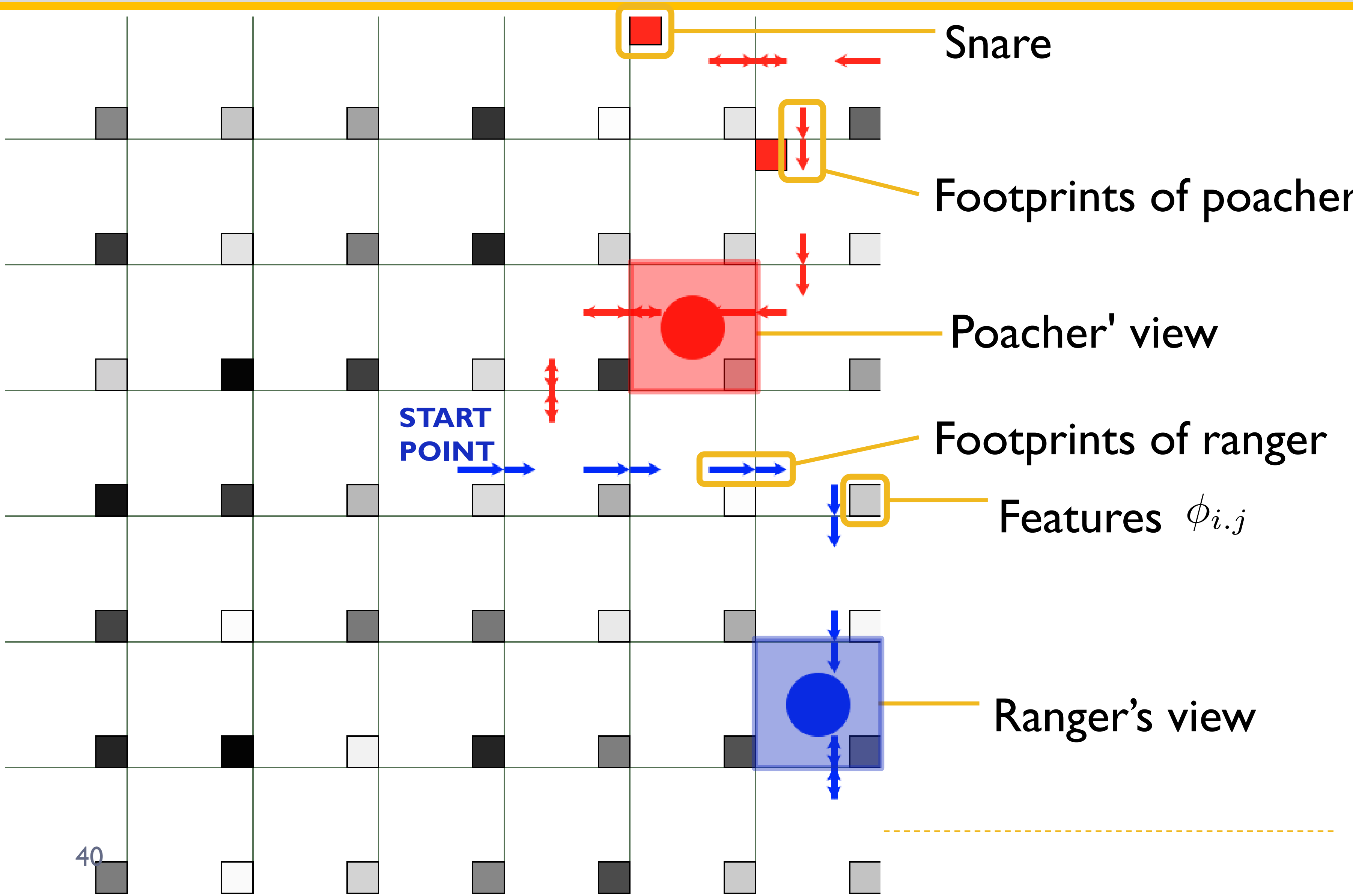
Lighters

Poacher camp

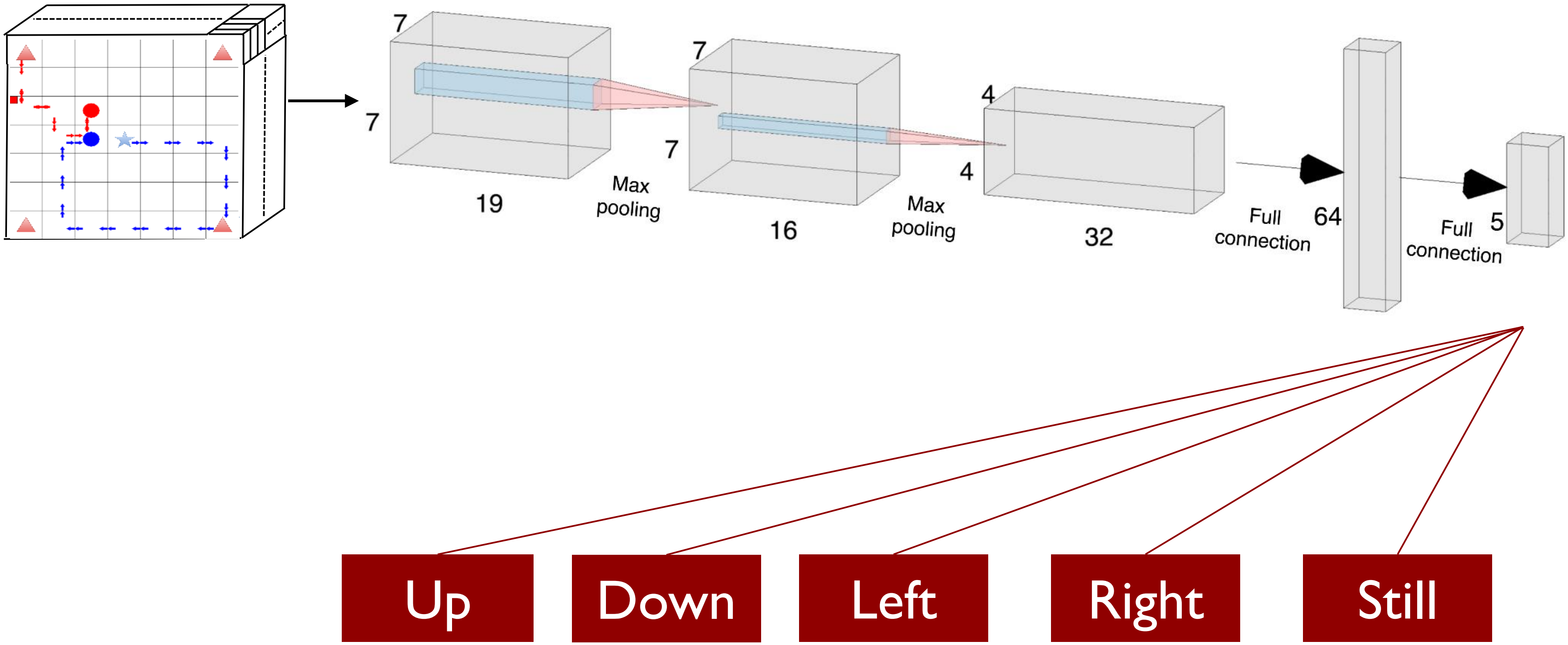
Tree marking

Deep Reinforcement Learning for Green Security Games with Real-Time Information Yufei Wang, Zheyuan Ryan Shi, Lantao Yu, Yi Wu, Rohit Singh, Lucas Joppa, Fei Fang In AAAI-19

Markov Game Formulation

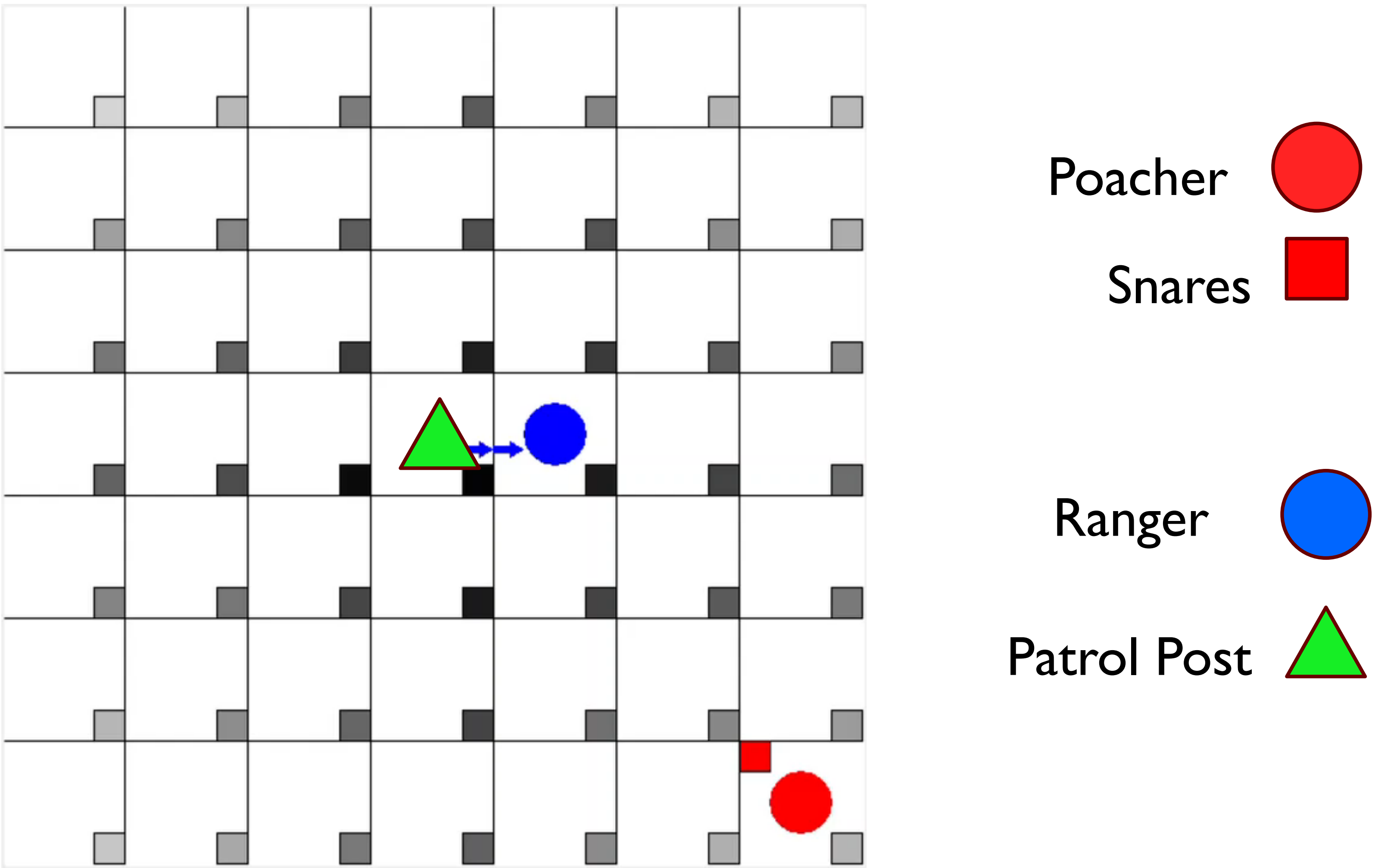


Deep Q Network Trained Against Heuristic Poacher



- Deep Q Network (DQN): Game state → Q-value

Deep Q Network Trained Against Heuristic Poacher



Approximate Equilibrium: DQN + Double Oracle

Compute $\sigma^d, \sigma^a = Nash(G^d, G^a)$

Compute Nash/Minimax

Train $f^d = DQN(\sigma^a)$

Train a new DQN that best responds to poacher's strategy

Train $f^a = DQN(\sigma^a)$

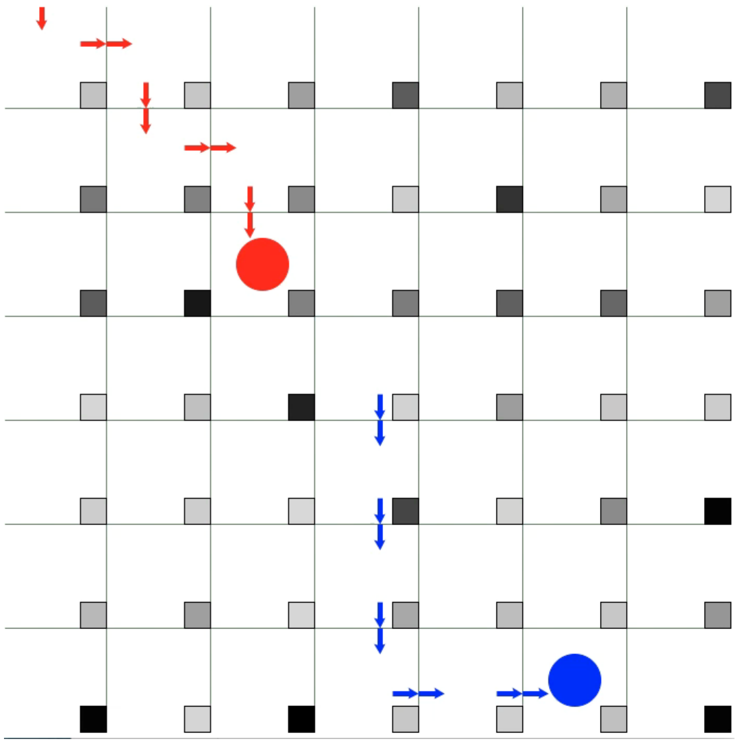
Train a new DQN that best responds to ranger's strategy

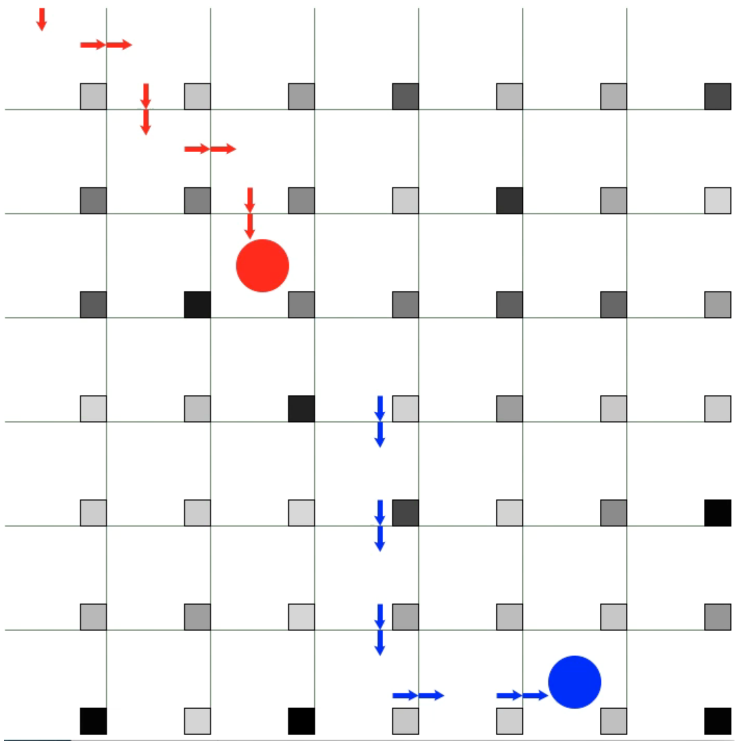
Add f^d, f^a to G^d, G^a

Update sets of DQNs

Enhancements

- Use local modes for efficient training
- Start with domain-specific heuristic strategies





New Research Challenges Arise

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- UAV & human coordinated patrols
- Community engagement
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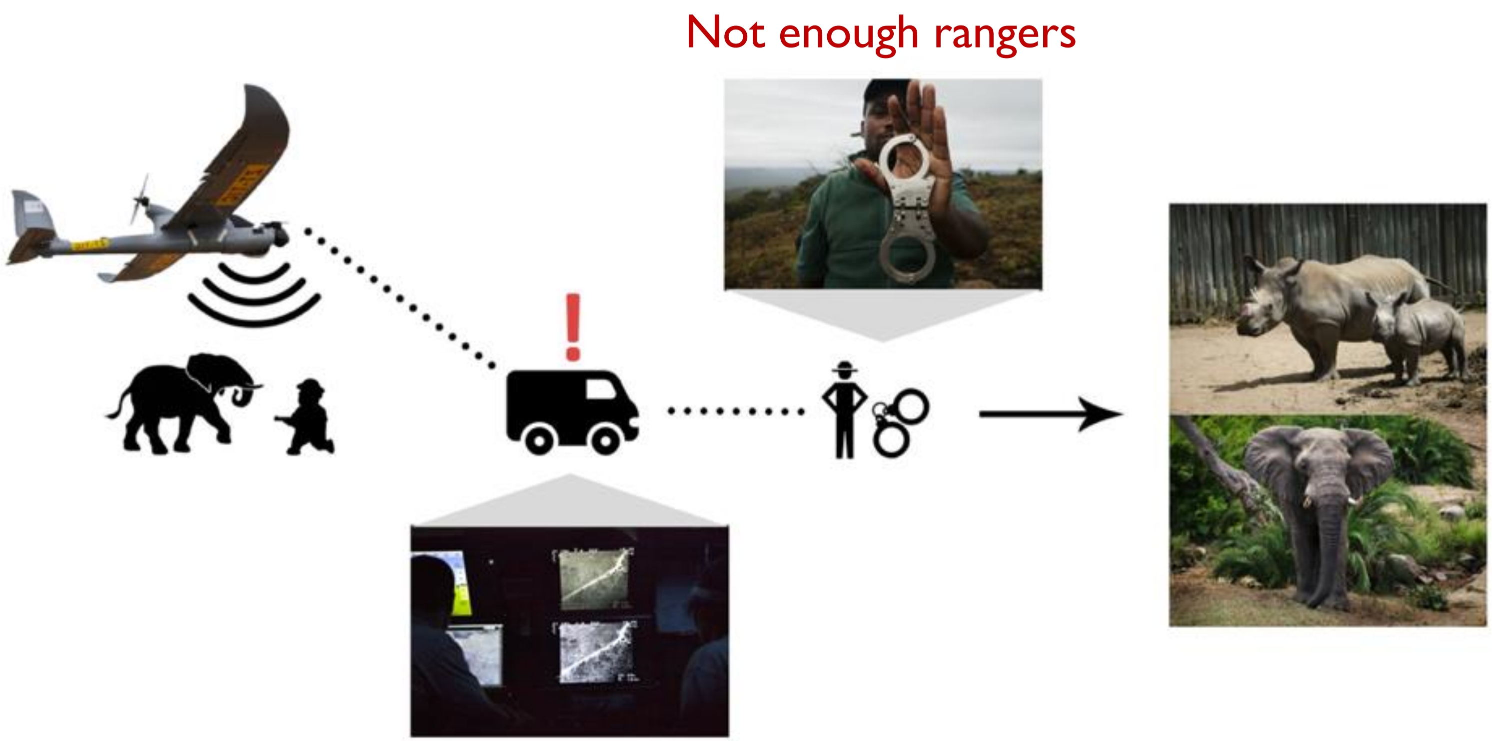
UAV & Human Patrols in Anti-Poaching



Field Test in Botswana

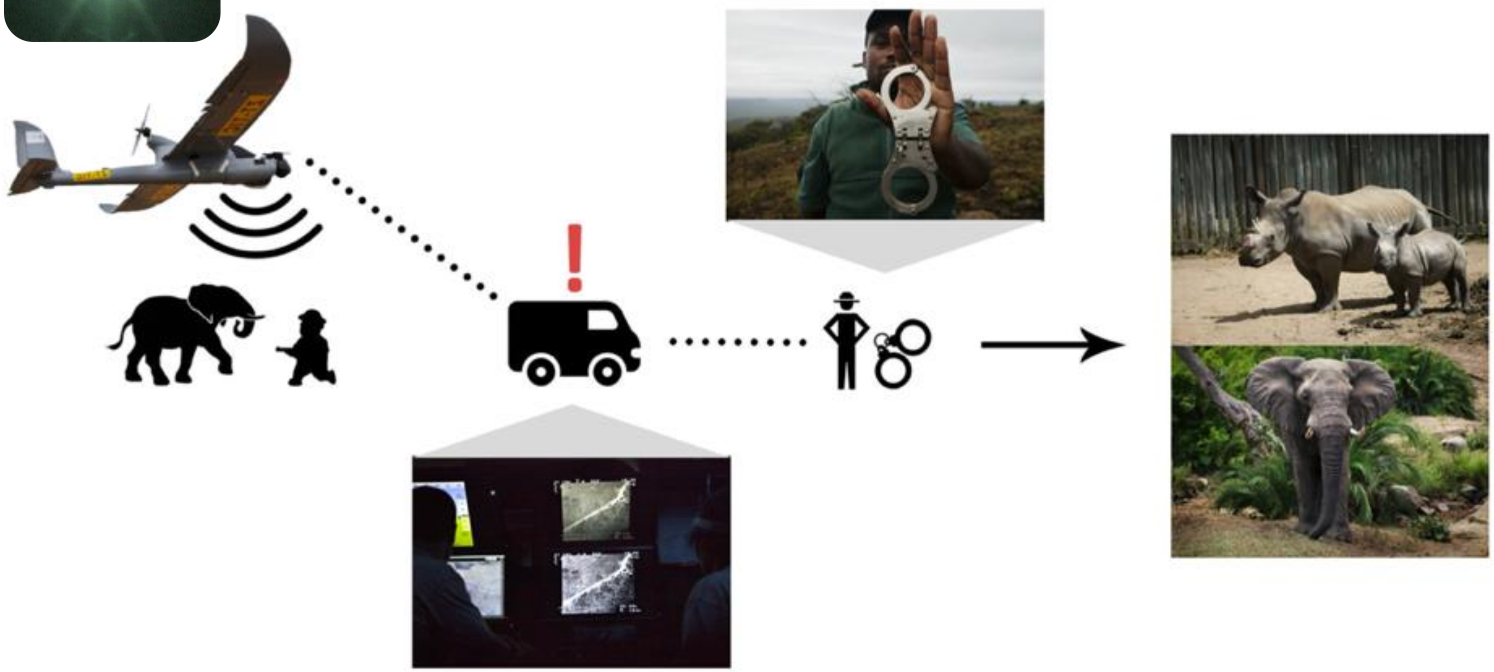
47 SPOT Poachers in Action: Augmenting Conservation Drones with Automatic Detection in Near Real Time. Elizabeth Bondi, Fei Fang, Mark Hamilton, Debarun Kar, Donnabell Dmello, Jongmoo Choi, Robert Hannaford, Arvind Iyer, Lucas Joppa, Milind Tambe, Ram Nevatia. In IAAI-18

UAV & Human Patrols in Anti-Poaching

Actual video of poacher running away

Flash light to deter poachers

Not enough rangers



Bondi et al., To Signal or Not To Signal: Exploiting Uncertain Real-Time Information in Signaling Games for Security and Sustainability. AAAI 2020

New Research Challenges Arise

- Patrol with real-time information
- UAV & human coordinated patrols
- Community engagement
- Zoning & Fine policy design

Huang et al., Green security game with community engagement. AAMAS 2020.
Shen et al., When to Follow the Tip: Security Games with Strategic Informants. IJCAI 2020.
Shi et al., Designing the Game to Play: Optimizing Payoff Structure in Security Games. IJCAI 2018.

Summary: AI for Anti-Poaching

- Our work
  - First time using deep learning and deep reinforcement learning in security games
  - Successful field tests and tool available to hundreds of sites world wide

- Related problems
  - Illegal logging, illegal mining, overfishing
  - Learn from limited and imbalanced data
  - Efficient learning algorithm to solve large-scale games

Machine Learning + Game Theory for Societal Challenges

Security & Safety

Environmental Sustainability

Zero Hunger

Transportation

Artificial Intelligence

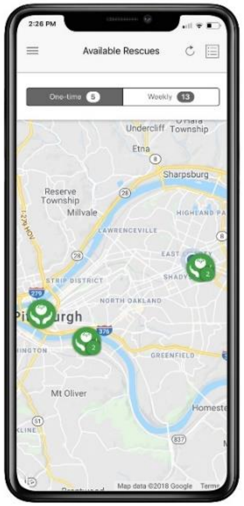
Computational Game Theory

Machine Learning

Societal Challenges

Volunteer-Based Food Rescue Platform

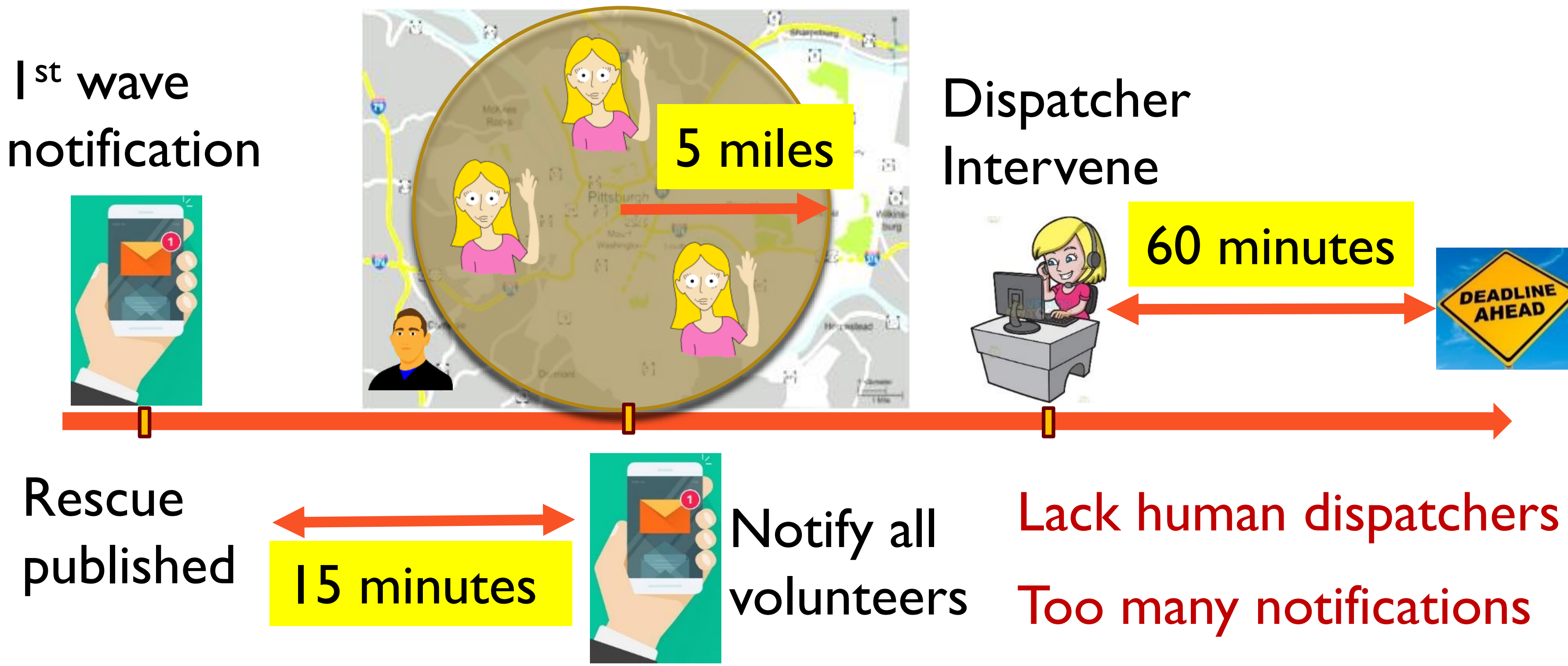
- Food waste and food insecurity coexist
  - Waste up to 40% food globally
  - 1 in 8 people go hungry every day
- Rescue good food!



In collaboration with 412 Food Rescue (412FR)

Problem: How to improve operational efficiency?

- Decision makers: donors, recipients, volunteers, platform
- Uncertainty about whether a rescue will be claimed



Predictive Model of Rescue Claim Status

- Determine which rescues need special attention

	Features
Timing	Fastest travel time of rescue
	Travel distance of rescue
	Weight of the food
	Time of day
	Time Slot
Weather	Precipitation
	Snowfall
	Average temperature
Location	AVs in donor's cell
	Average AVs in donor's neighboring cells
	AVs in recipient's cell
	AVs in donor and recipient's cells with vehicle

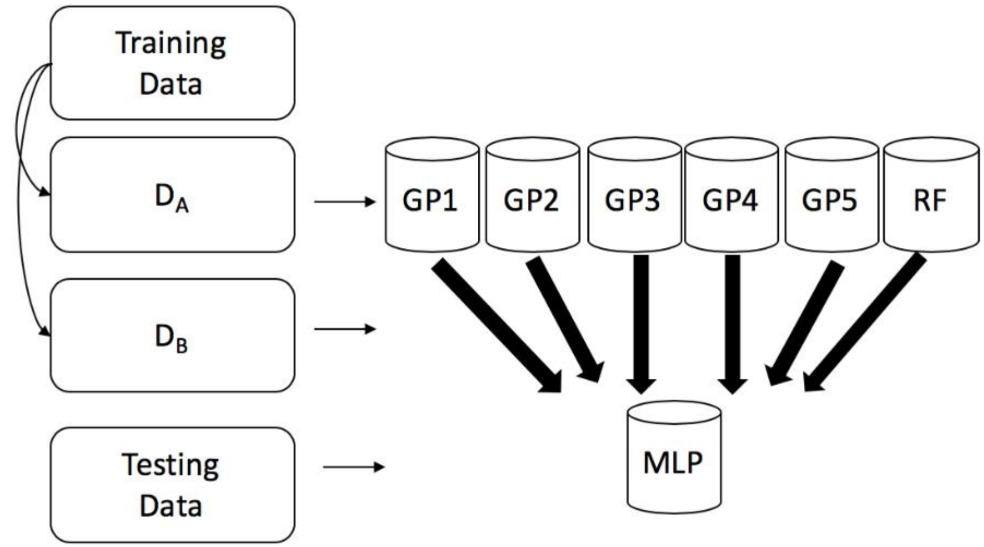
Positive label: Claimed

Negative label: Not claimed

Improving Efficiency of Volunteer-Based Food Rescue Operations. Zheyuan Ryan Shi∗, Yiwen Yuan∗, Kimberly Lo, Leah Lizarondo, Fei Fang. In IAAI-20.

Predictive Model of Rescue Claim Status

- Training data
  - May 2018 to Dec 2018
- Test data
  - Jan 2019 to May 2019

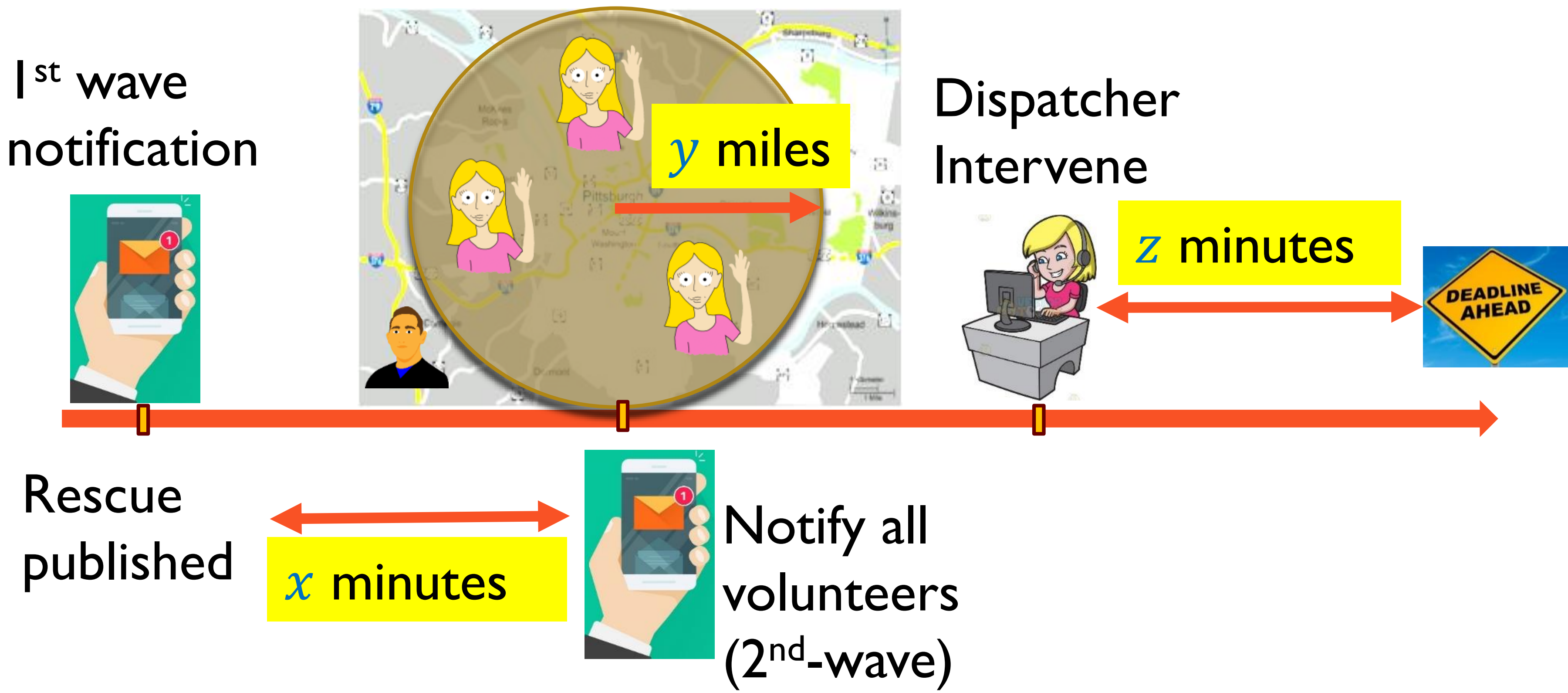


Model	Accuracy	Precision	Recall	F1	AUC
Gradient boosting	0.73	0.86	0.82	0.84	0.51
Random forest	0.71	0.87	0.78	0.82	0.54
Gaussian process	0.56	0.88	0.54	0.67	0.60
Stacking model	0.69	1.00*	0.64	0.78	0.81

Improving Efficiency of Volunteer-Based Food Rescue Operations. Zheyuan Ryan Shi∗, Yiwen Yuan∗, Kimberly Lo, Leah Lizarondo, Fei Fang. In IAAI-20.

Optimize Intervention and Notification Scheme

- Avoid excessive notifications
- Reduce human dispatcher's work load



Improving Efficiency of Volunteer-Based Food Rescue Operations. Zheyuan Ryan Shi∗, Yiwen Yuan∗, Kimberly Lo, Leah Lizarondo, Fei Fang. In IAAI-20.

Optimize Intervention and Notification Scheme

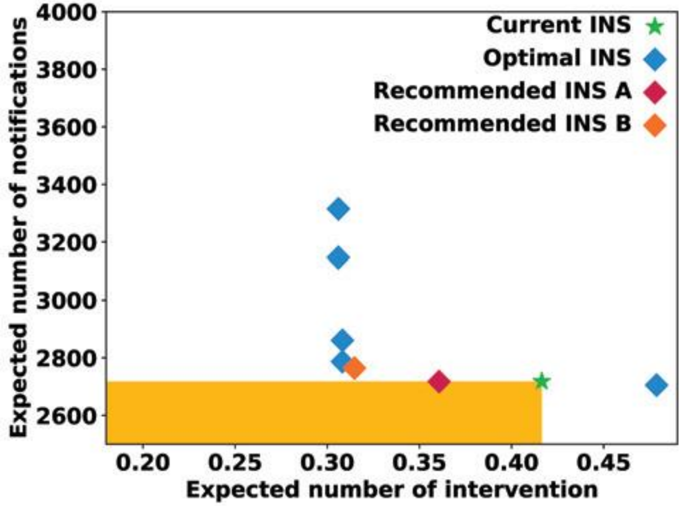
$$\min_{x,y,z} \quad \text{Expected \# of volunteer notifications} + \lambda \times \text{Expected \# of human interventions}$$

$$\text{s.t. Claim rate} \geq \text{threshold}$$

Solve using branch-and-bound

Optimize Intervention and Notification Scheme

- Optimize on data from May 2018 to Dec 2018
- Test on data from Jan 2019 to May 2019
- Checking Pareto frontier



INS	Interventions	Notifications
A: (16.5, 5.5, 45)	−13% (−0.06)	0% (−1)
B: (15.5, 5.5, 32.5)	−24% (−0.10)	+2% (+46)

Deployed since Feb 2020

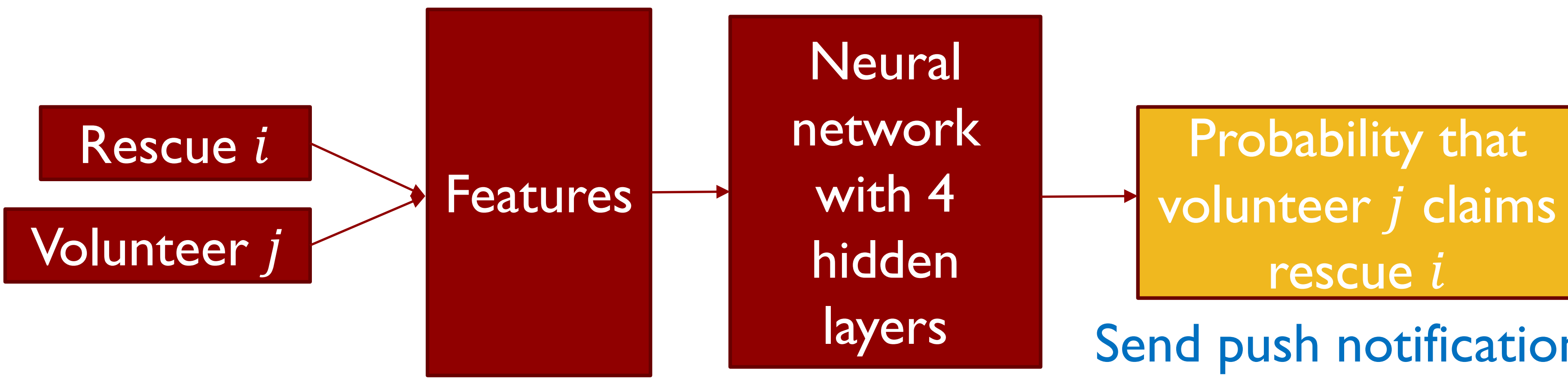
Optimize Intervention and Notification Scheme

- Preliminary result
  - Higher claim rate, lower claim time, less notifications
  - May exist many confounding factors

Condition	Claim Rate	Average time from publish to claim (min)	Average # of push notifications sent
Before 2/10/2020 (Previous scheme)	0.84	78.43	11499.45
2/10/2020-3/1/2020 (New scheme)	0.88	43.05	9167.52
After 3/1/2020 (After COVID)	0.92	39.73	9735.54

Rescue-Specific Notification Scheme

- Send 1st-wave notifications to volunteers that are more likely to claim the rescue
- Recommend volunteers to rescue requests



Send push notifications to top k volunteers

A Recommender System for Crowdsourcing Food Rescue Platforms. Zheyuan Ryan Shi, Leah Lizarondo, Fei Fang In WWW-21

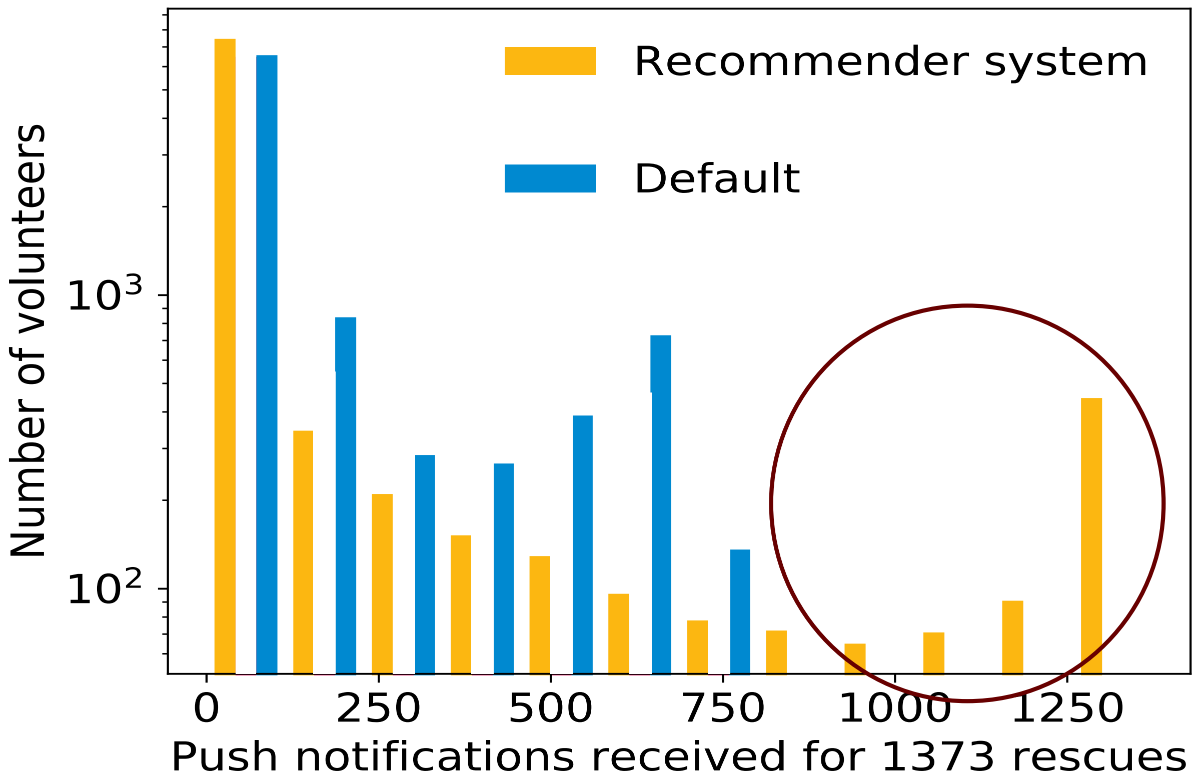
Evaluation

- Metric: Hit ratio at top k (HR@k): % of rescues that are claimed by volunteers in top k
- $k = 964$ (to match the default notification scheme)

Model	HR@k (SD)
NN	**0.7269 (0.0310)**
RF(1:1)	0.5989 (0.0395)
RF(1:20)	0.6035 (0.0511)
GBDT(1:1)	0.6235 (0.0549)
GBDT(1:20)	0.5394 (0.0152)
SM(1:1)	0.4996 (0.0005)
SM(1:20)	0.5219 (0.0125)
Default	0.4392 (N/A)

Caveat with Rescue-Specific Notification

- ML model discovers some frequent volunteers and sends them notifications almost all the time



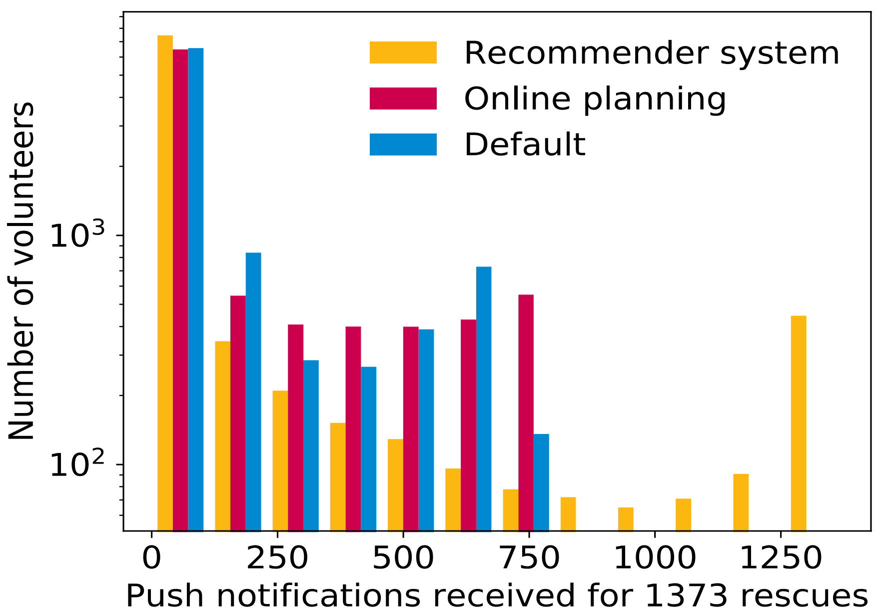
Machine Learning + Online Planning

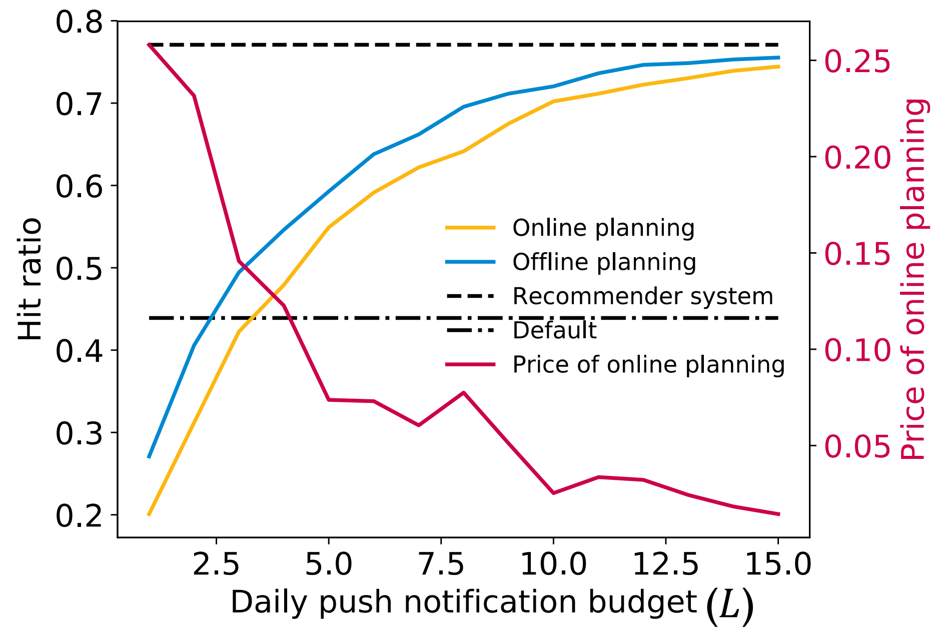
- Each volunteer receives at most L notifications per day
- For current rescue i, determine who to send notifications to by planning with an projected set of future rescues R

$$
\begin{aligned}
\max_{x} \quad & \sum_{j \in V} \left(p_{ij} x_{ij} + \sum_{i' \in R} p_{i'j} x_{i'j} \right) \\
s.t. \quad & \sum_{j \in V} x_{i'j} \leq k, \quad \forall i' \in R \\
& \sum_{j \in V} x_{ij} \leq k \\
& x_{ij} + \sum_{i' \in R} x_{i'j} \leq b_j, \quad \forall j \in V \\
& x_{ij} \in \{0, 1\}, \quad \forall i \in R, \forall j \in V
\end{aligned}
$$

Evaluation

- Avoid the over-concentration with $L = 5$
- Hit ratio at top k = 0.65 (current practice = 0.44)
- In-field test: will start in weeks!





Summary: AI for Zero Hunger

- Our work
  - First to use recommender system + online planning for notification in volunteer-based platforms
  - Deployed in the real world

- Open research questions
  - Game-theoretic model with volunteers' strategic thinking
  - Recommend a route with multiple rescues

Takeaway 1: Many Ways to Integrate ML and Game Theory

- Data-based game theoretic reasoning

- Learning-powered equilibrium computation

- More…
  - End-to-end learning in games
  - Multi-agent reinforcement learning
  - Adversarial machine learning
  - …

Takeaway 2: AI Has Great Potential for Social Good

Security & Safety


Environmental Sustainability




Zero Hunger

Transportation

Artificial Intelligence

Computational Game Theory

Machine Learning

Societal Challenges

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CyLab