SECURITY GAMES

Key Algorithmic Principles, Deployed Systems, Research Challenges

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SECURITY GAMES

Key Algorithmic Principles, Deployed Systems, Research Challenges

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GLOBAL CHALLENGES FOR SECURITY

Game Theory for Security Resource Optimization

EXAMPLE MODEL: STACKELBERG SECURITY GAMES

Security Allocation:

- **Targets have weights**
- **Adversary surveillance**

Adversary

Defender

	Target #1	Target #2
Target #1	**4, -3**	**-1, 1**
Target #2	**-5, 5**	**2, -1**

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Adversary

Defender

	Target #1	Target #2
Target #1	4, -3	-1, 1
Target #2	-5, 5	2, -1

EXAMPLE MODEL: STACKELBERG SECURITY GAMES

Security Resource Optimization: Not 100% Security

Random Strategy: Increase cost/uncertainty to attackers

Stackelberg Game: Defender "moves" first; adversary responds after surveillance

Challenges faced: Massive scale games; difficult for a human planner

Adversary

Defender

	Target #1	Target #2
Target #1	**4, -3**	**-1, 1**
Target #2	**-5, 5**	**2, -1**

SECURITY GAMES: RESEARCH & APPLICATION

Game Theory + Optimization + Uncertainty + Learning + …

- Massive-scale games
- Reason with uncertainty

- Learn adversary behavior from data
- Repeated Games
- + Conservation Biology, Criminology

Infrastructure Security Games


Coast Guard

Coast Guard: Ferry


LAX

TSA


LA Sheriff


USC

Argentina Airport


Chile Border

Green Security Games

Coast Guard


Panthera/WWF

IBM

Opportunistic Crime Games

Cyber Security Games

ARMORWAY: Founded 2013


Jain


Pita

Los Angeles Unified School District Police

Glendale PD

Los Angeles Sheriff's Department

University of Southern California

Huntington Ingalis Industries

US Coast Guard

RAND Corporation

Oakland Airport

GLOBAL PRESENCE OF SECURITY GAMES EFFORTS

MILIND TAMBE'S ARMOR AND ITS MANY ITERATIONS ARE USED AROUND THE WORLD TO PROTECT AGAINST TERRORISM, POACHERS, ILLEGAL FISHING AND OTHER THREATS.

DEPLOYED

Ports — PROTECT
PROTECT intelligently randomizes U.S. Coast Guard patrols to optimize scarce resources to secure crowded piers, bridges and ferry terminals.
PROTECT is employed at:
Port of New York and New Jersey
Port of Boston
Port of Houston
Port of Los Angeles-Long Beach

Staten Island Ferry — PROTECT
PROTECT provides protection to the Staten Island Ferry, which carries up to 4,000 passengers at peak times.

Los Angeles International Airport — ARMOR
ARMOR intelligently randomizes schedules of checkpoints along the five roads that lead into the airport.

U.S. Air Traffic — IRIS
As part of its multipronged strategy to prevent attacks, the Transportation Security Administration (TSA) has since 2009 deployed Milind Tambe's IRIS system, which intelligently randomizes federal air marshals' flight schedules to make their air patrols unpredictable to would-be malefactors.

SUCCESSFULLY TESTED

Gulf of Mexico (Near Corpus Christi, Texas) — ARMOR-FISH
ARMOR-FISH intelligently randomized schedules for U.S. Coast Guard aerial patrols to thwart the illegal fishing of decimated shark and red snapper populations. (2014)

Los Angeles Metro — TRUSTS
The Los Angeles Sheriff's Department, which LA Metro subcontracts for security, employed TRUSTS to intelligently randomize patrol schedules to stop fare evasion. The Sheriff's Department later ran preliminary experiments to ascertain effectiveness in deploying scarce police personnel to deter crime and terrorism on LA Metro. (2011–2013)

Uganda — PAWS
Ugandan rangers tested PAWS at Queen Elizabeth National Park to intelligently randomize patrols to prevent the slaughter of animals, including Cape buffalo, waterbuck and giant forest hogs, which are served up locally and exported as "bush meat." (2014)

Malaysia — PAWS
Panthera, an NGO that is committed to ensuring the survival of tigers and other wild cats, in conjunction with the nonprofit group Rimba, began testing PAWS in forests in northeastern Malaysia, to evaluate its ability to generate effective patrols in the challenging, hilly terrain. (2014)

POSSIBLE FUTURE TEST SITES

Vietnam, Cambodia, Bangladesh, Indonesia — PAWS

island nation.

Madagascar — PAWS
Milind Tambe, working with Meredith Gore, an associate professor of conservation social sciences at Michigan State University, and a Malagasy civil society group called Alliance Voahary Gasy (AVG), hopes to eventually employ PAWS in Madagascar to randomize patrol schedules for rangers, police and national park officials to reduce environmental crimes, especially illegal logging.

KEY LESSONS: SECURITY GAMES

Decision aids based on computational game theory in daily use

Optimize limited security resources against adversaries

Application yield research challenges: Key advances in security games

Scale-up: Incremental strategy generation & Marginals

Uncertainty: Integrate MDPs, Robustness

Human Behavior: Model innovations based on quantal response

Current applications: Global, interdisciplinary challenges

Green security games: criminology, computation, conservation

OUTLINE: SECURITY GAMES RESEARCH (2007- ONGOING)

Infrastructure Security Games

Green Security Games

Opportunistic Crime Security Games

Air Travel

2007

Ports

2011

Trains

2013

Fisheries

2014

Wildlife

2016

Urban Crime

2016

Evaluation I: AAAI, IJCAI, AAMAS papers…

Evaluation II: Real-world deployments (Patience)

ARMOR AIRPORT SECURITY: LAX [2007]

Basic “Stackelberg Security Game” Model

BASIC SECURITY GAME OPERATION [2007]

Basic “Stackelberg Security Game” Model

BASIC SECURITY GAME OPERATION [2007]


Pita


Paruchuri

Using ARMOR as an example

	Target #1	Target #2	Target #3
Defender #1	2, -1	-3, 4	-3, 4
Defender #2	-3, 3	3, -2	….
Defender #3	….	….	….

Mixed Integer Program

Pr (Canine patrol, 8 AM @Terminals 2,5,6) = 0.17

Canine Team Schedule, July 28

	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8
8 AM		Team1			Team3	Team5		
9 AM			Team1	Team2				Team4
10 AM		Team3		Team5		Team2		
…	…	…	…	…	…	…	…	…

SECURITY GAME MIP [2007]


Pita


Paruchuri

Generate Mixed Strategy for Defender in ARMOR

	Target #1	Target #2	Target #3
Defender #1	2, -1	-3, 4	-3, 4
Defender #2	-3, 3	3, -2	….
Defender #3	….	….	….

$$\max \sum_{i \in X} \sum_{j \in Q} R_{ij} \times x_i \times q_j$$ ← Maximize defender expected utility

$$s.t. \quad \sum_i x_i = 1$$ ← Defender mixed strategy

$$\sum_{j \in Q} q_j = 1$$ ← Adversary response

$$0 \le (a - \sum_{i \in X} C_{ij} x_i) \le (1 - q_j) M$$ ← Adversary best response

SECURITY GAME PAYOFFS [2007]

Previous Research Provides Payoffs in Security Game Domains

	Target #1	Target #2	Target #3
Defender #1	2, -1	-3, 4	-3, 4
Defender #2	-3, 3	3, -2	….
Defender #3	….	….	….

+ Handling Uncertainty

$$\max \sum_{i \in X} \sum_{j \in Q} R_{ij} \times x_i \times q_j$$

Maximize defender expected utility

ARMOR AIRPORT SECURITY: LAX [2008]

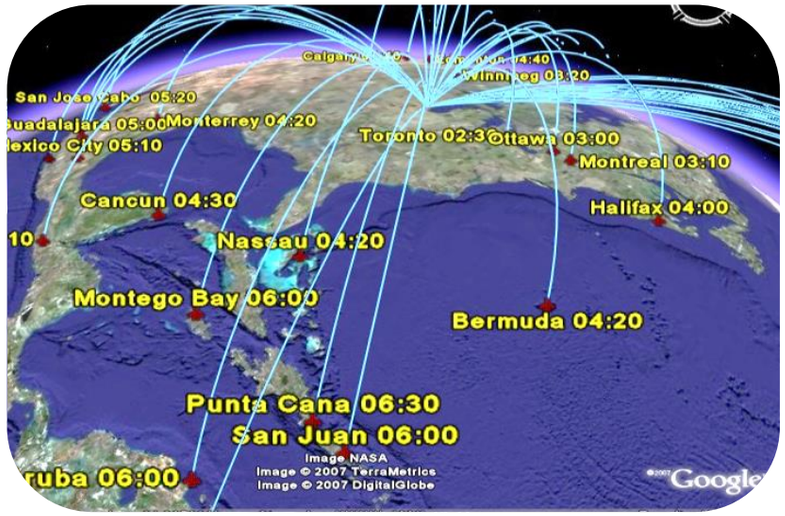
Congressional Subcommittee Hearings

IRIS: FEDERAL AIR MARSHALS SERVICE [2009]

Visiting TSA Freedom Center

IRIS: FEDERAL AIR MARSHALS SERVICE [2009]

Scale Up Number of Defender Strategies



	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Strategy 1	ARMOR Actions: ~100			
Strategy 2				
Strategy 3				
Strategy 4				

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Strategy 1	IRIS 1000 flights/day Actions: ~10^{41}			
Strategy 2				
Strategy 3				
Strategy 4				

- **ARMOR runs out of memory**
- **Incremental strategy generation: Not enumerate 10^{41} actions**

IRIS: SCALE UP [2009]


Jain


Kiekintveld

Why Scale-up is Difficult

1000 flights, 20 air marshals:

10^{41} combinations

$$\max_{x,q} \sum_{i \in X} \sum_{j \in Q} R_{ij} x_i q_j$$

$$s.t. \sum_i x_i = 1, \sum_{j \in Q} q_j = 1$$

$$0 \le (a - \sum_{i \in X} C_{ij} x_i) \le (1 - q_j) M$$

	Attack 1	Attack 2	Attack …	Attack 1000
1 ,2, 3 ..	5,-10	4,-8	⋯	-20,9
1, 2, 4 ..	5,-10	4,-8	⋯	-20,9
1, 3, 5 ..	5,-10	-9,5	⋯	-20,9
…				
…	**10^{41} rows**			

IRIS: SCALE UP [2009]


Jain


Kiekintveld

Small Support Set for Mixed Strategies

Small support set size:
Most x_i variables zero

1000 flights, 20 air marshals:

10^{41} combinations

	Attack 1	Attack 2	Attack …	Attack 1000
~~$X_{123} = 0.0$~~	~~1 ,2, 3 ..~~	~~5,-10~~	~~4,-8~~	~~…~~	~~-20,9~~
$X_{124} = 0.239$	1, 2, 4 ..	5,-10	4,-8	…	-20,9
~~$X_{135} = 0.0$~~	~~1, 3, 5 ..~~	~~5, 10~~	~~9,5~~	~~…~~	~~20,9~~
$X_{378} = 0.123$	…				
	… ←	**10^{41} rows**			

IRIS: INCREMENTAL STRATEGY GENERATION


Jain


Kiekintveld

Exploit Small Support

Master

	Attack 1	Attack 2	…	Attack 6
1,2,4	5,-10	4,-8	…	-20,9

Slave (LP Duality Theory)
Best new pure strategy

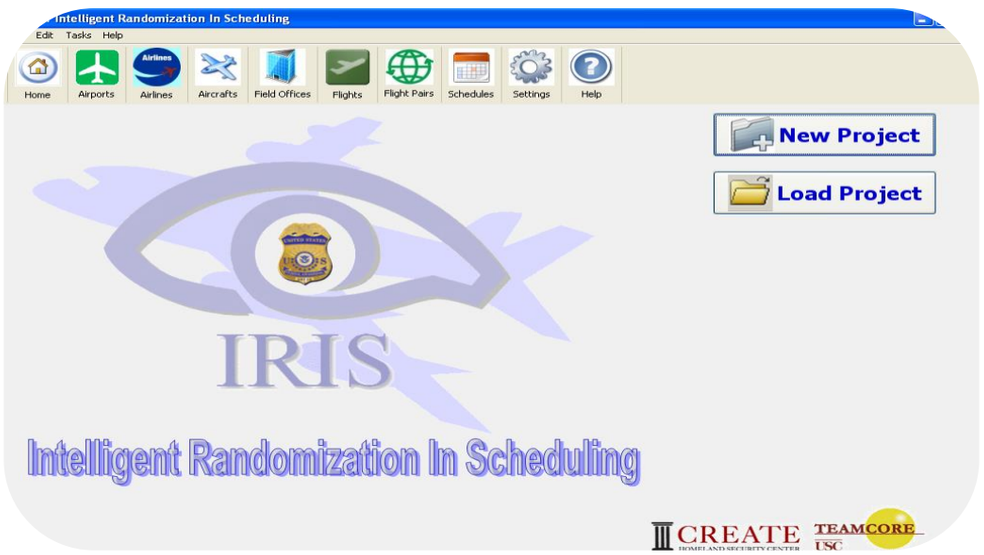
	Attack 1	Attack 2	…	Attack 6
1,2,4	5,-10	4,-8	…	-20,9
3,7,8	-8, 10	-8,10	…	-8,10

Global Optimal

	Attack 1	Attack 2	…	Attack 6
1,2,4	5			-20,9
3,7,8	-8			-8,10
…				

500 rows
NOT 10^{41}

IRIS: DEPLOYED FAMS [2009-]



Significant change in FAMS operations

"…in 2011, the Military Operations Research Society selected a USC project with FAMS on randomizing flight schedules for the prestigious Rist Award…"

R. S. Bray (TSA)
Statement before Transportation Security Subcommittee
US House of Representatives 2012

PROTECT: PORT PROTECTION PATROLS DEPLOYED [2011-]

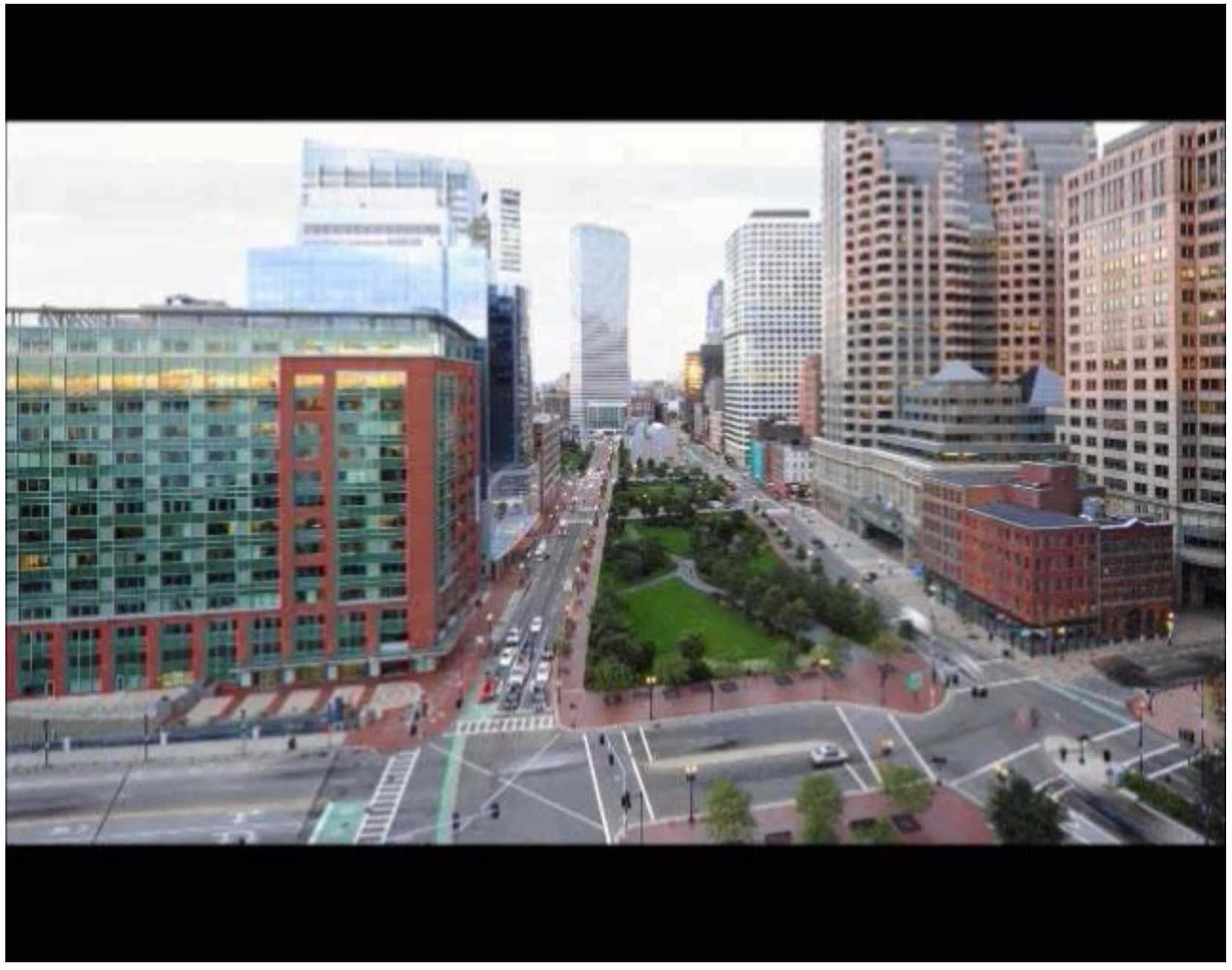
Using “Marginals” for Scale-up

USS Cole after attack

French oil tanker hit by small boat

PROTECT: PORT PROTECTION PATROLS DEPLOYED [2011-]

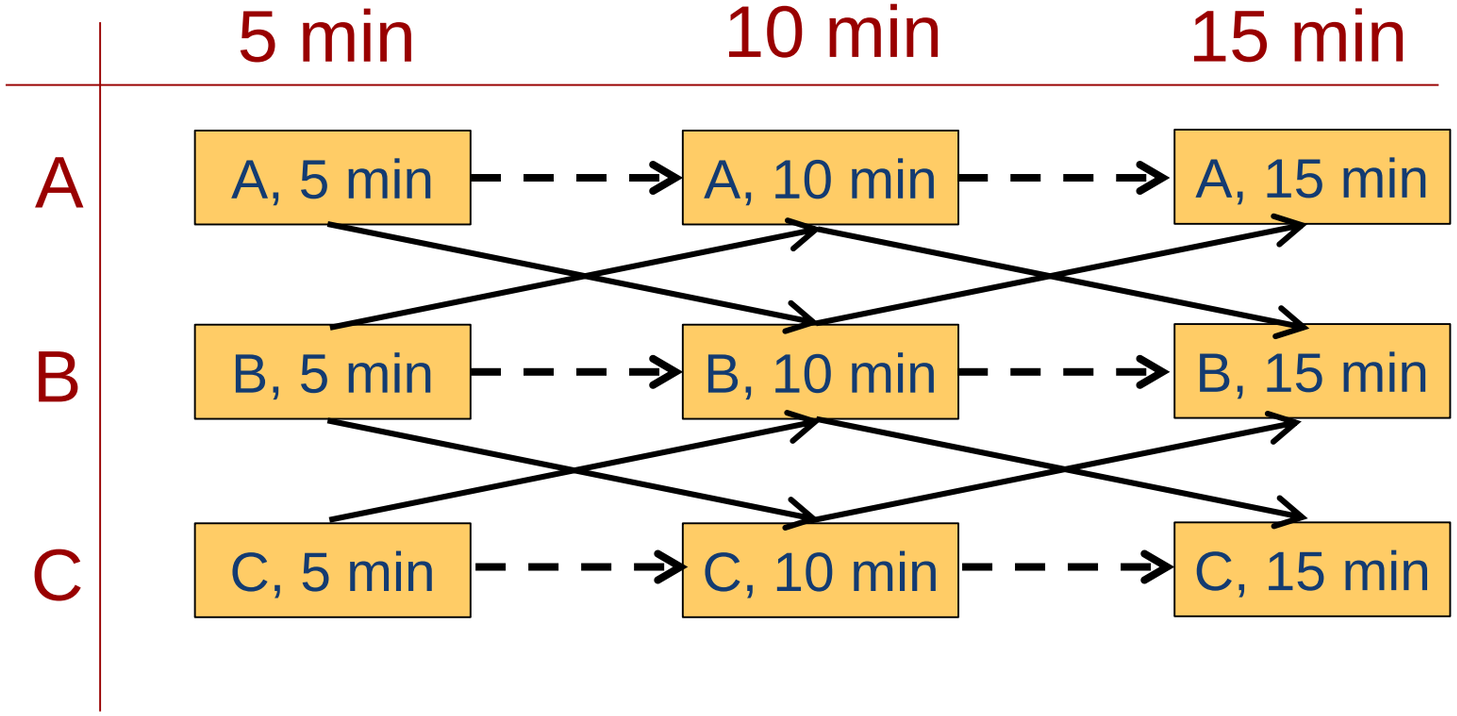
Using “Marginals” for Scale-up



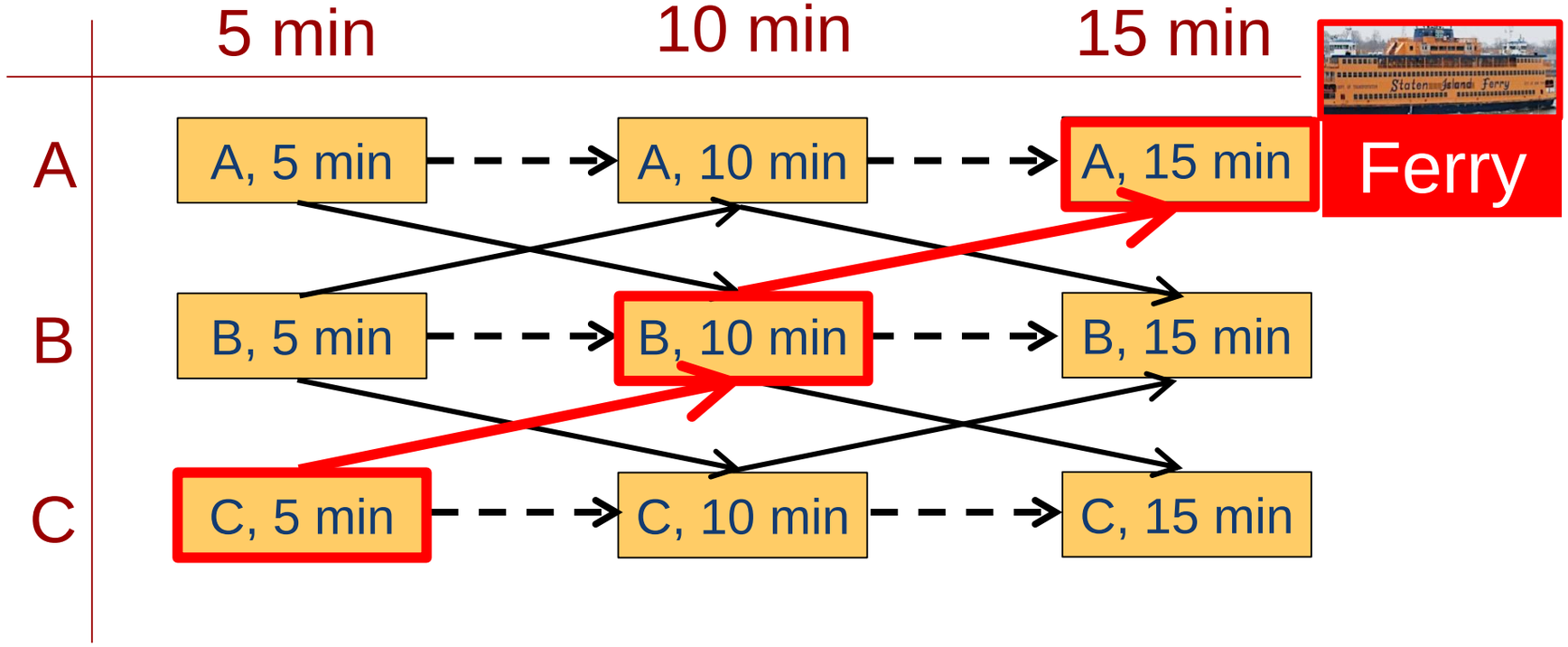
PROTECT: FERRY PROTECTION DEPLOYED [2013-]

Using “Marginals” for Scale-up

Transition Graph Representation

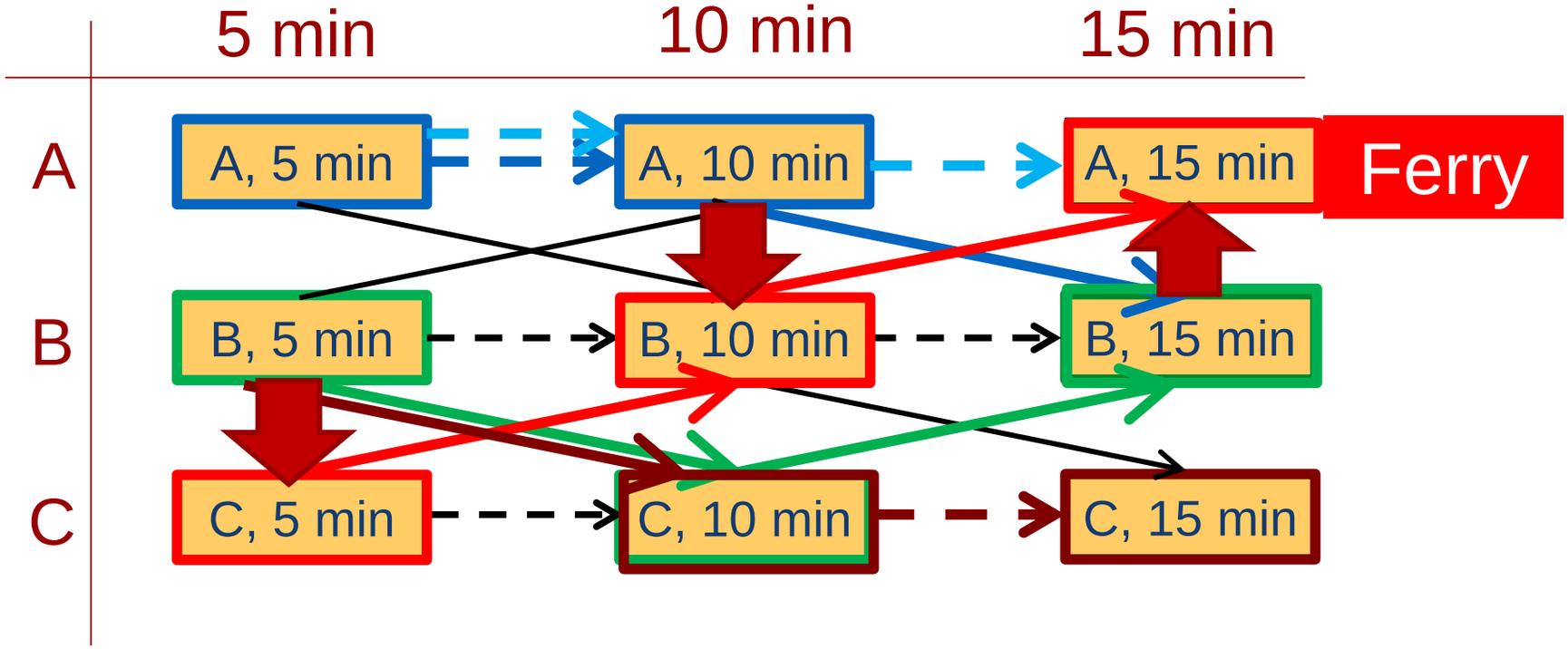


Transition Graph Representation



FERRIES: PATROL ROUTES AS VARIABLES

Patrols protect nearby ferry location; Solve as done in ARMOR



FERRIES: PATROL ROUTES AS VARIABLES


Fang


Jiang

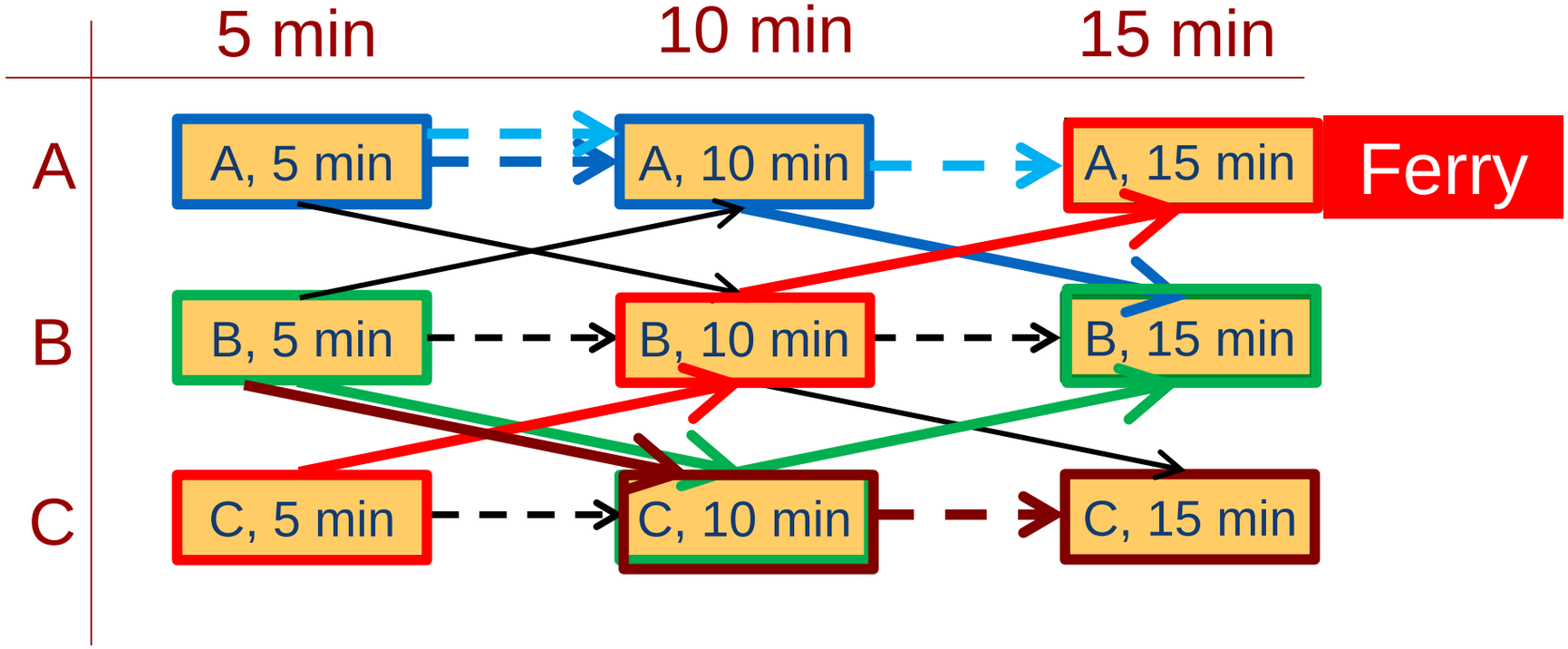

Kiekintveld

Exponential Numbers of Patrol Routes

Patrols protect nearby ferry location; Solve as done in ARMOR

- Pr ([(B,5), (C, 10), (C,15)]) = 0.47
- Pr ([(B,5), (C,10), (B,15)]) = 0.23
- Pr ([(A,5), (A,10), (B,15)]) = 0.17
- Pr ([(A,5), (A,10), (A,15)]) = 0.13

N^T variables



FERRIES: SCALE UP

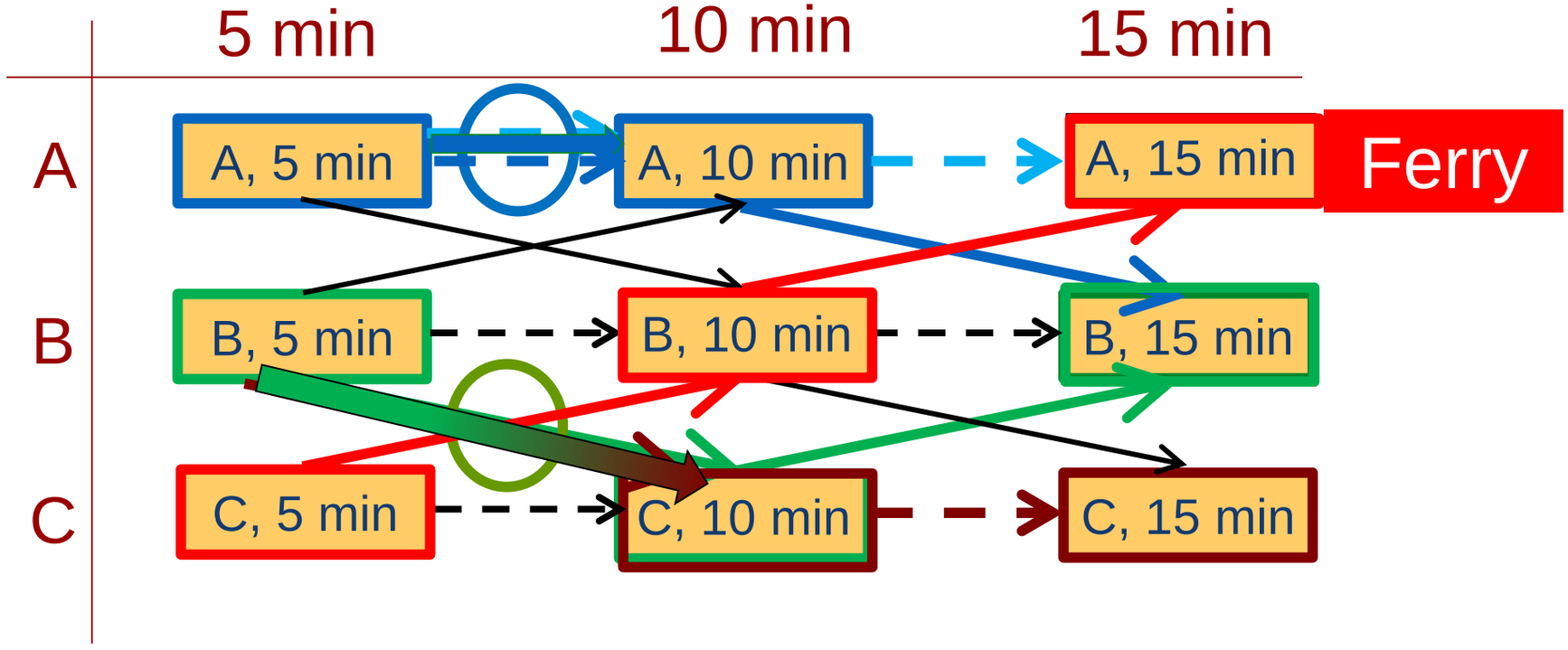

Fang


Jiang


Kiekintveld

Marginal Probabilities Over Segments

Variables: NOT routes, but probability flow over each segment

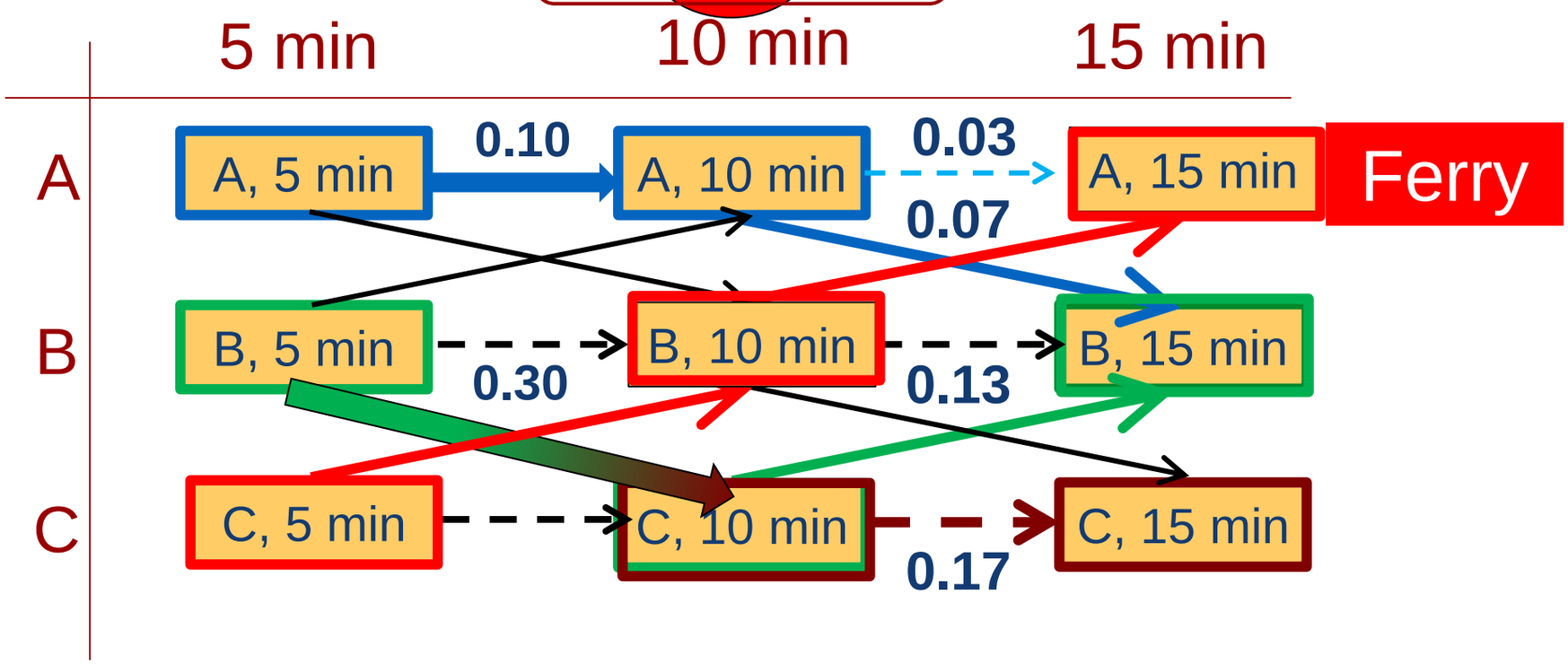


Obtain Marginal Probabilities Over Segments

$N^2.T$ variables

N^T variables

Extract: *Pr([(B,5), (C, 10), (C,15)]) = 0.47*
Pr([(B,5), (C,10), (B,15)]) =0.23



PROTECT: FERRY PROTECTION DEPLOYED [2013-]

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- Not vetted for CNN

Posted September 8, 2013 by

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

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

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PROTECT: PORT PROTECTION PATROLS [2013]

Congressional Subcommittee Hearing

OUTLINE: SECURITY GAMES RESEARCH (2007-)

Infrastructure Security Games

Air Travel

2007

Ports

2011

Trains

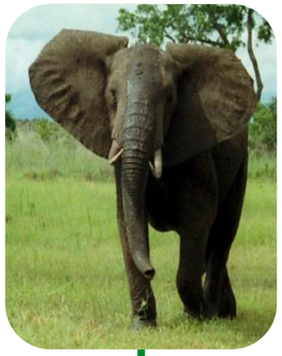
2013

Green Security Games

Fisheries

2014

Wildlife



2016

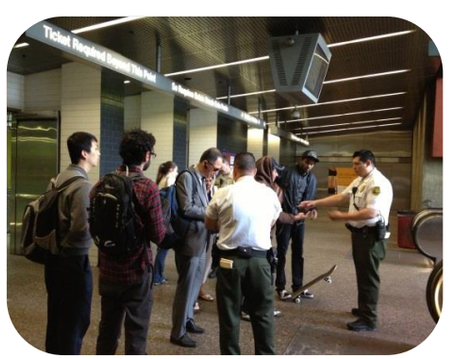
Opportunistic Crime Security Games

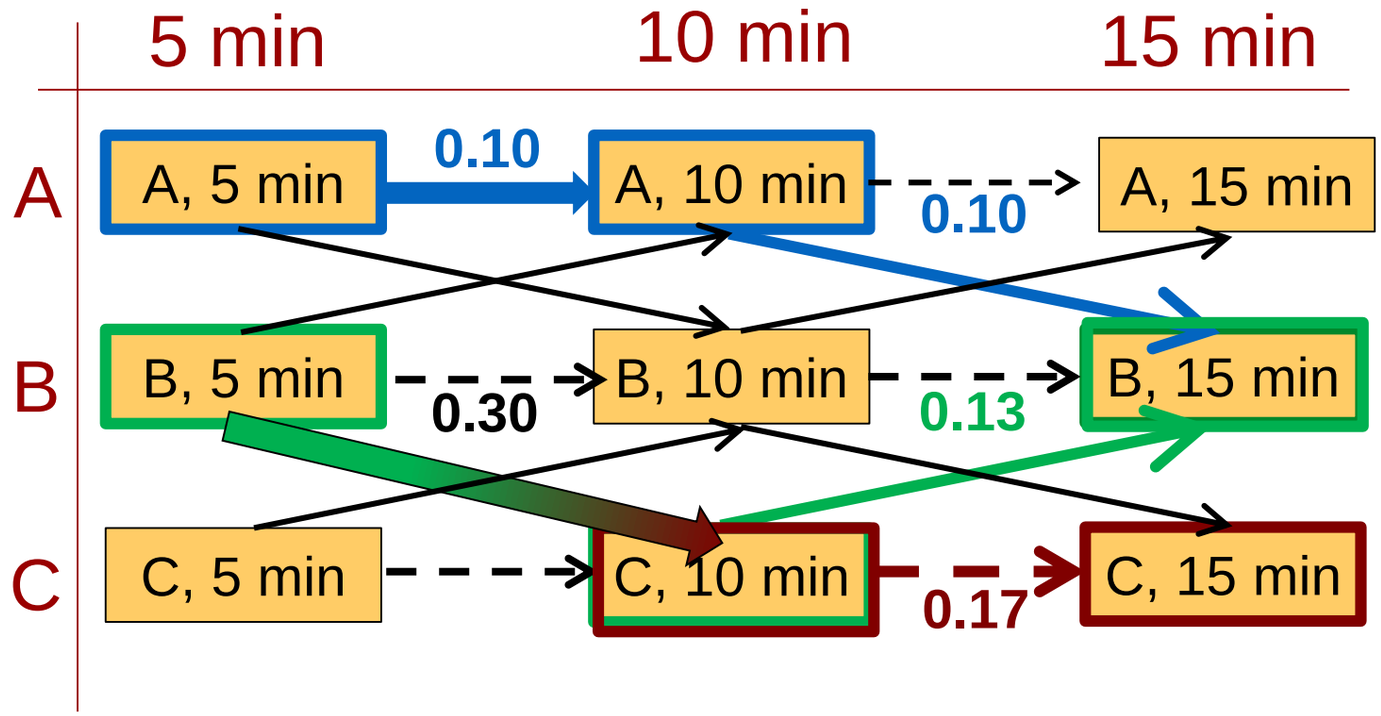
Urban Crime

2016

TRUSTS: FREQUENT ADVERSARY INTERACTION [2013]

Patrol Against Fare Evaders



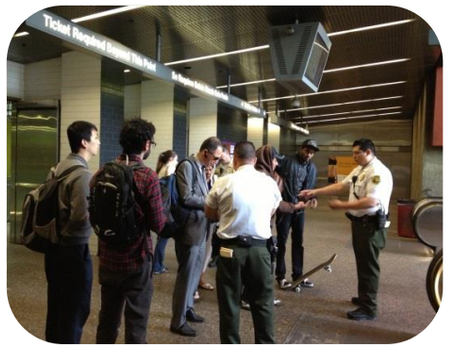


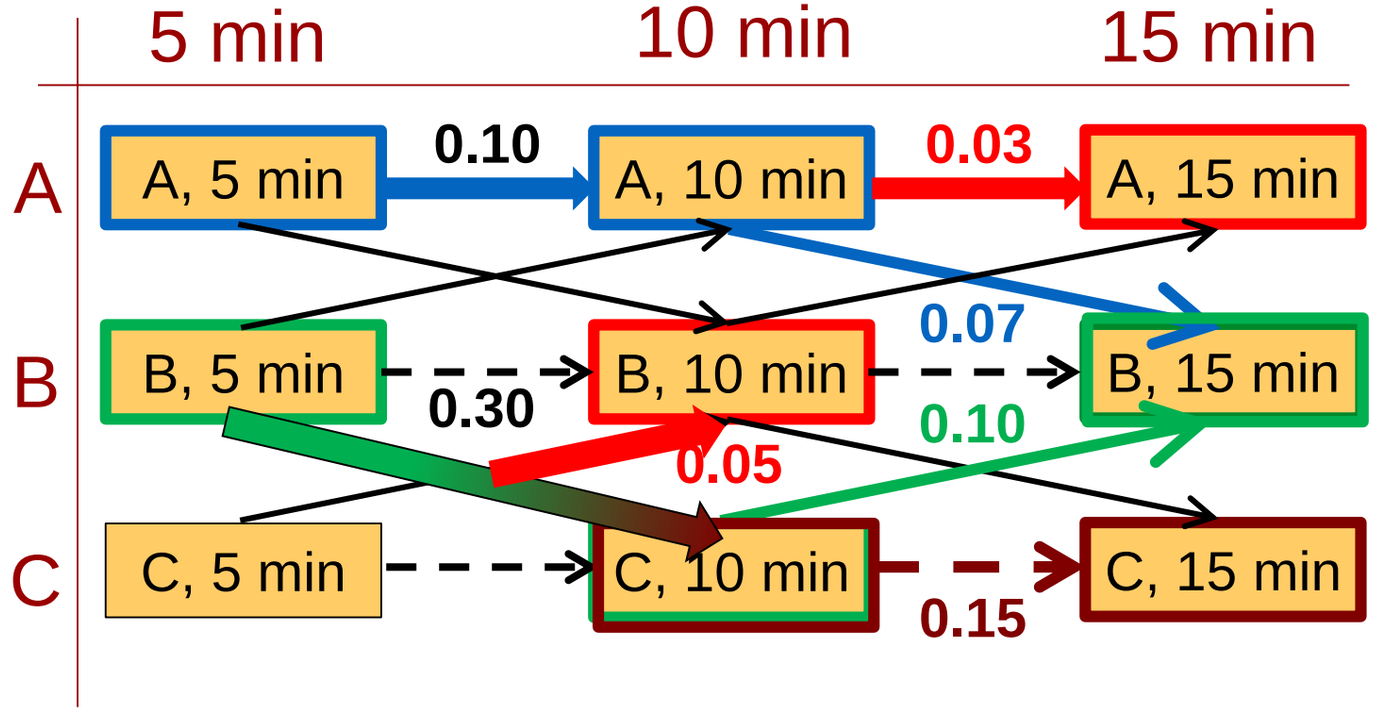
TRUSTS: PATROL AGAINST FARE EVADERS


Jiang


Delle Fave

Uncertainty in Defender Action Execution





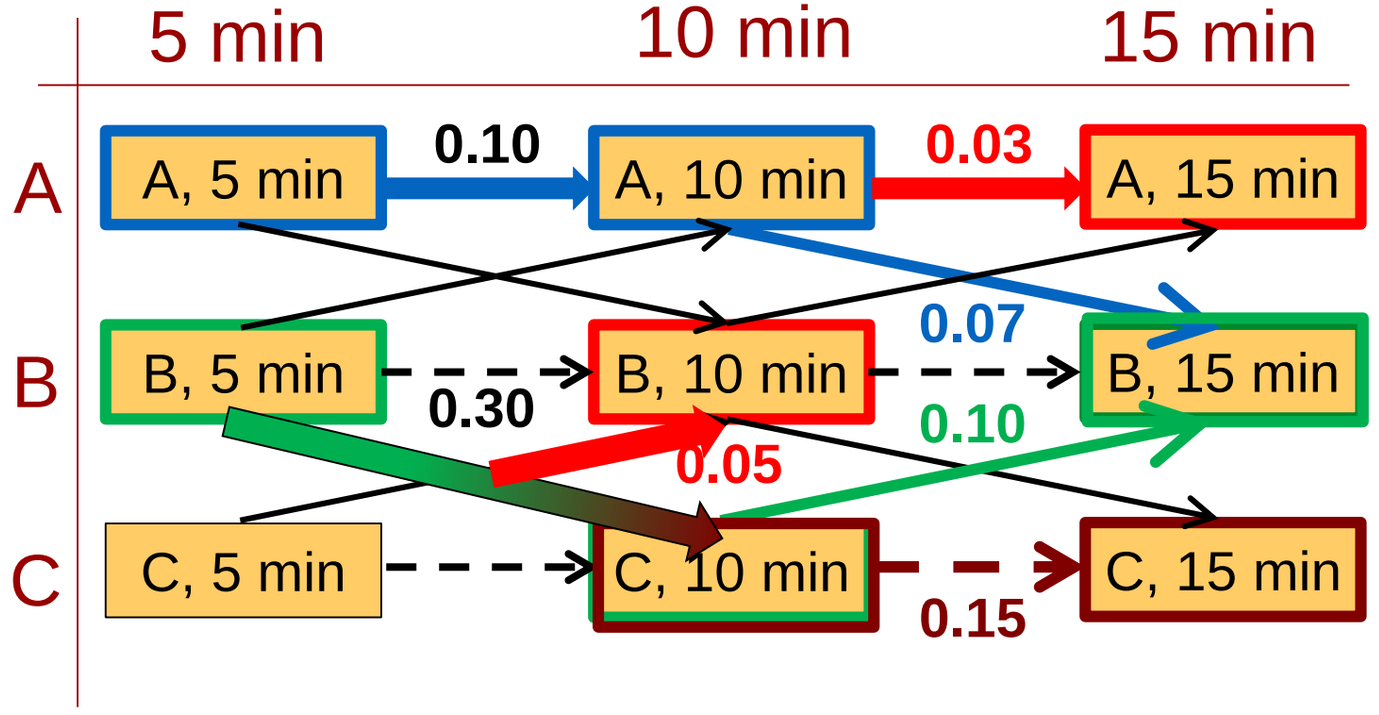
TRUSTS: PATROL AGAINST FARE EVADERS


Jiang


Delle Fave

Uncertainty in Defender Action Execution

Markov Decision Problems in Security Games



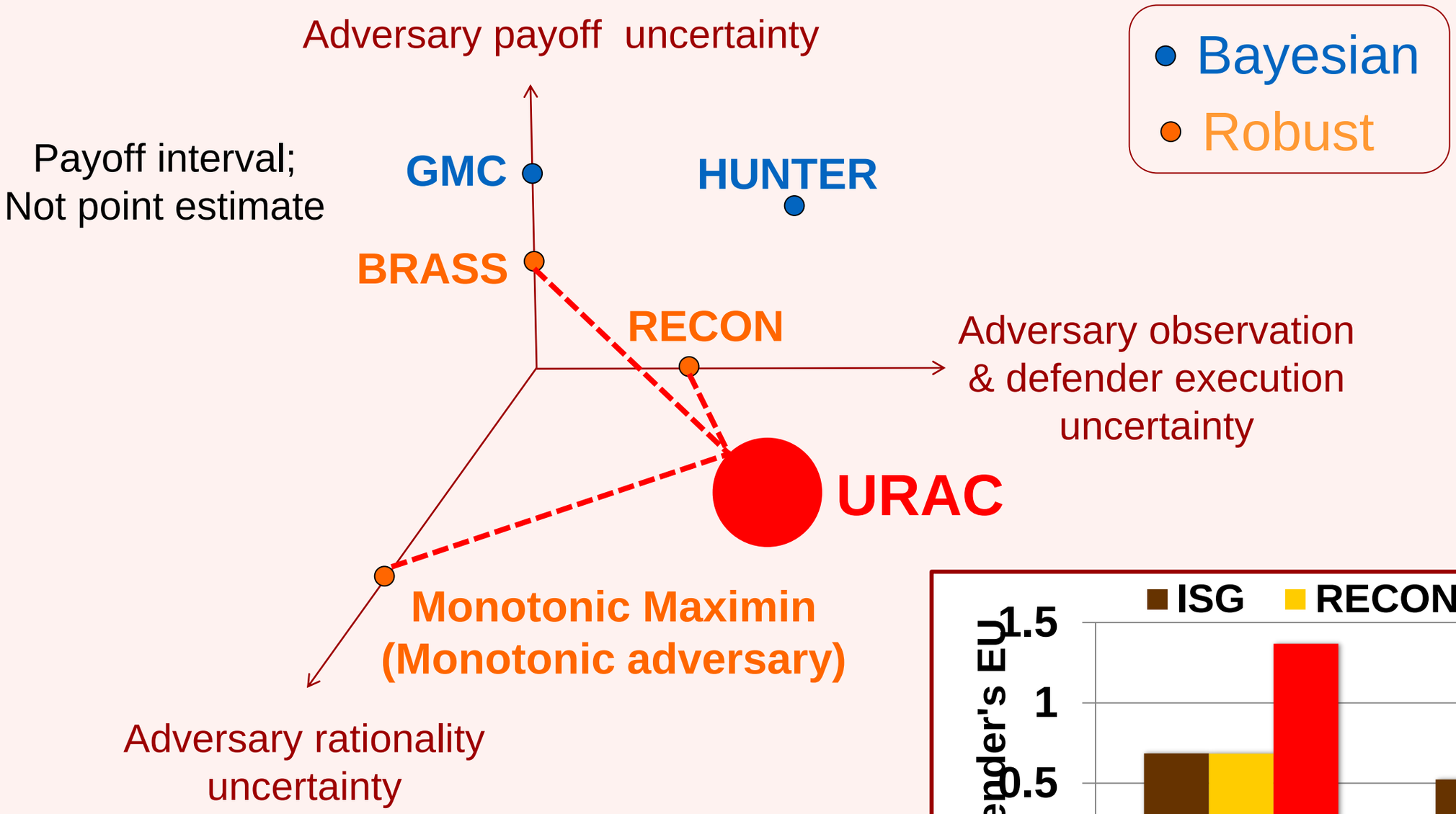
UNCERTAINTY SPACE ALGORITHMS

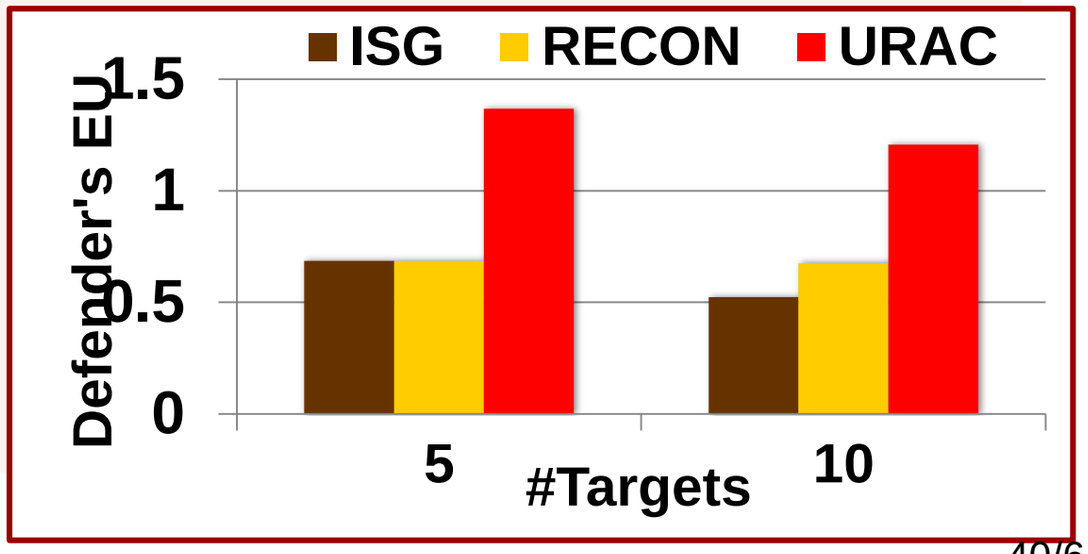

Yin


Nguyen


An

Bayesian and Robust Approaches





OUTLINE: SECURITY GAMES RESEARCH (2007-)

Infrastructure Security Games

Air Travel

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Trains

Green Security Games

Fisheries

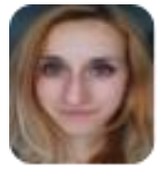
Wildlife

Opportunistic Crime Security Games

Urban Crime

2007 2011 2013 2014 2016 2016

GREEN SECURITY GAMES


McCarthy


Ford


Brown

Protecting Forest, Fish, Rivers and Wildlife

FOREST PROTECTION

FISHERY PROTECTION

RIVER POLLUTION PREVENTION

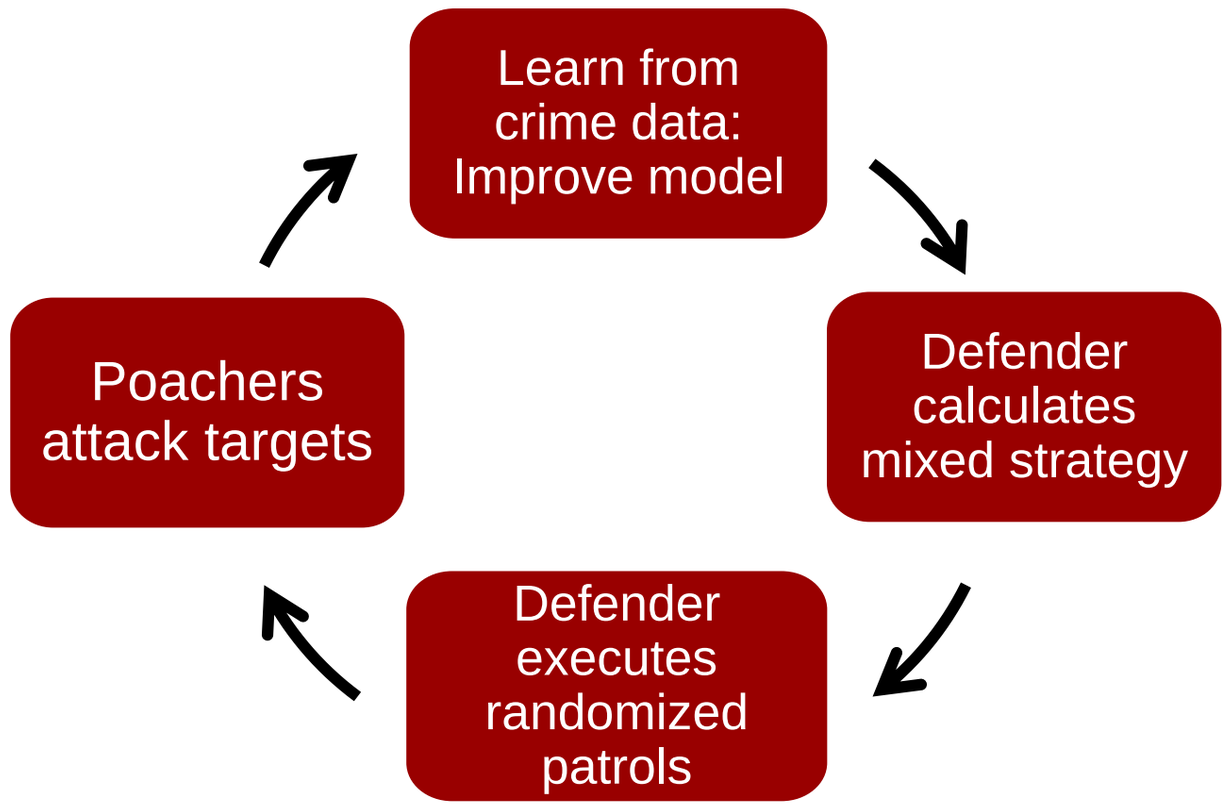
WILDLIFE PROTECTION

Murchison Falls National Park, Uganda

GREEN SECURITY GAMES

Repeated Stackelberg Game

Bounded rationality model of poachers

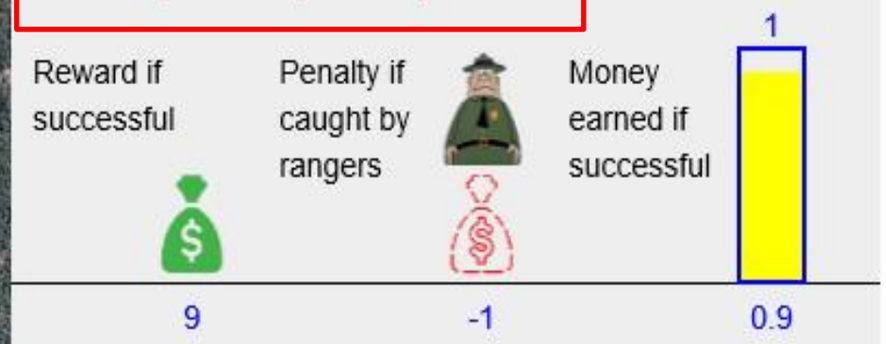


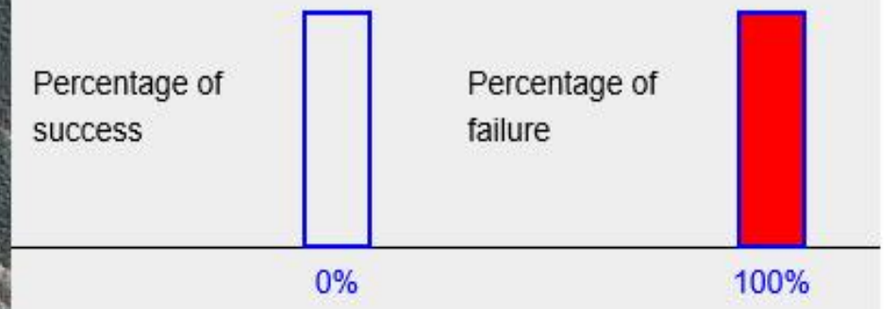

Kar

Human Subjects as Poachers

Game 2 Caught!

Total: $1.3 = $1.4 - $0.1





End Game

LESSON 1: QUANTAL RESPONSE [2011]


Pita

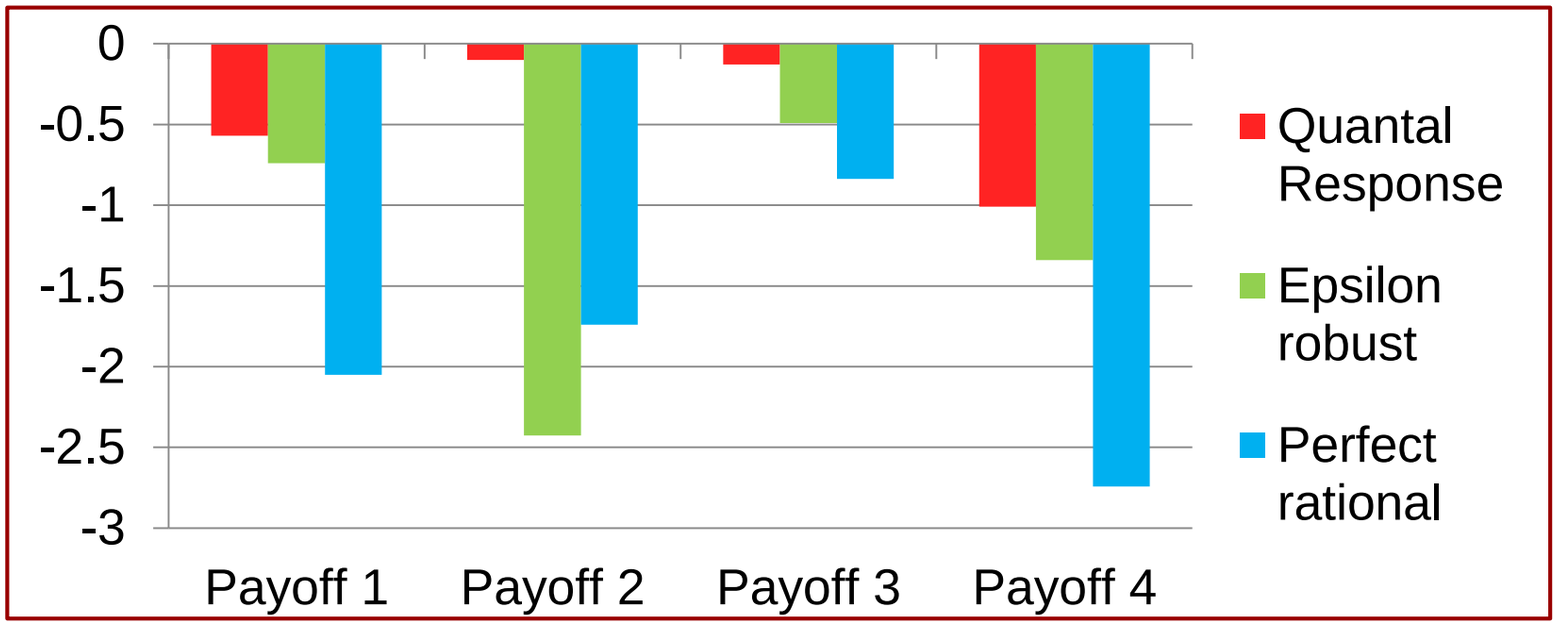

Yang

Models of Bounded Rationality

Perfect: $EU^{adversary}(j) = Capture\,\text{Prob} \times \text{Penalty} + (1 - Capture\,\text{Prob}) \times \text{Reward}$

Quantal Response(QR) [McFadden 73]: Stochastic Choice, Better Choice More likely

$$\text{Adversary's probability of } \textbf{choosing target j} = \frac{e^{\lambda \cdot (EU^{adversary}(x, j))}}{\sum_{j'=1}^{T} e^{\lambda \cdot (EU^{adversary}(x, j'))}}$$



LESSON 2: SUBJECTIVE UTILITY QUANTAL RESPONSE

Nguyen

Models of Bounded Rationality

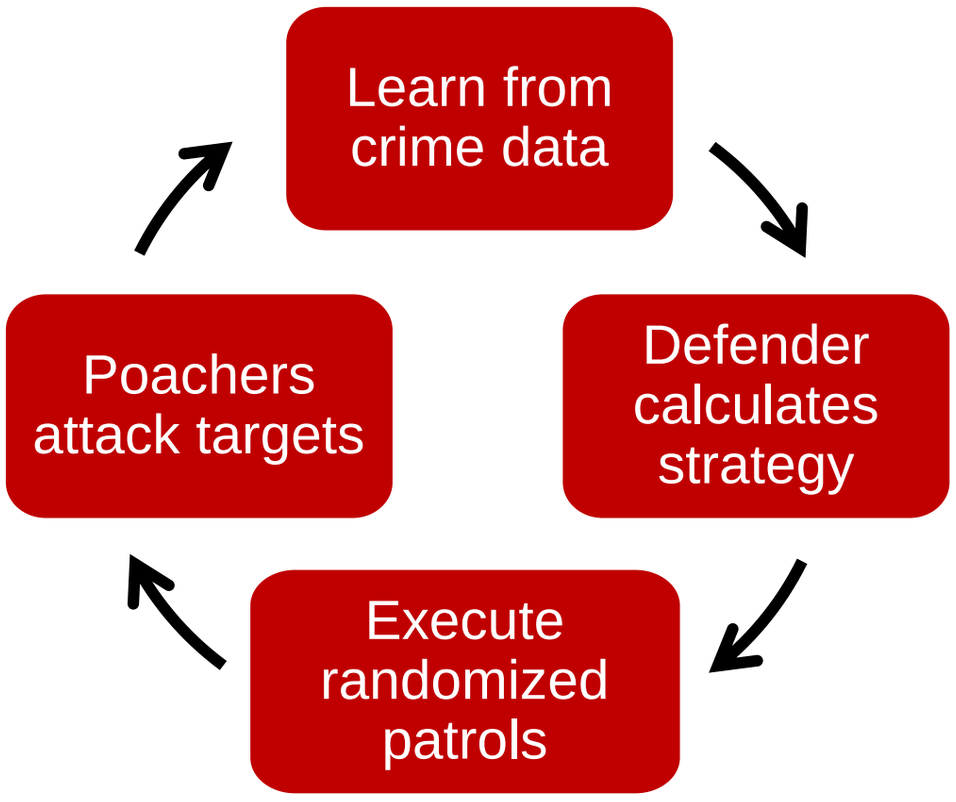
Subjective Utility Quantal Response(SUQR) [Nguyen 13]:

$$SEU^{adversary}(j) = w_1 \times Capture\,\text{Prob} + w_2 \times \text{Reward} + w_3 \times \text{Penalty}$$

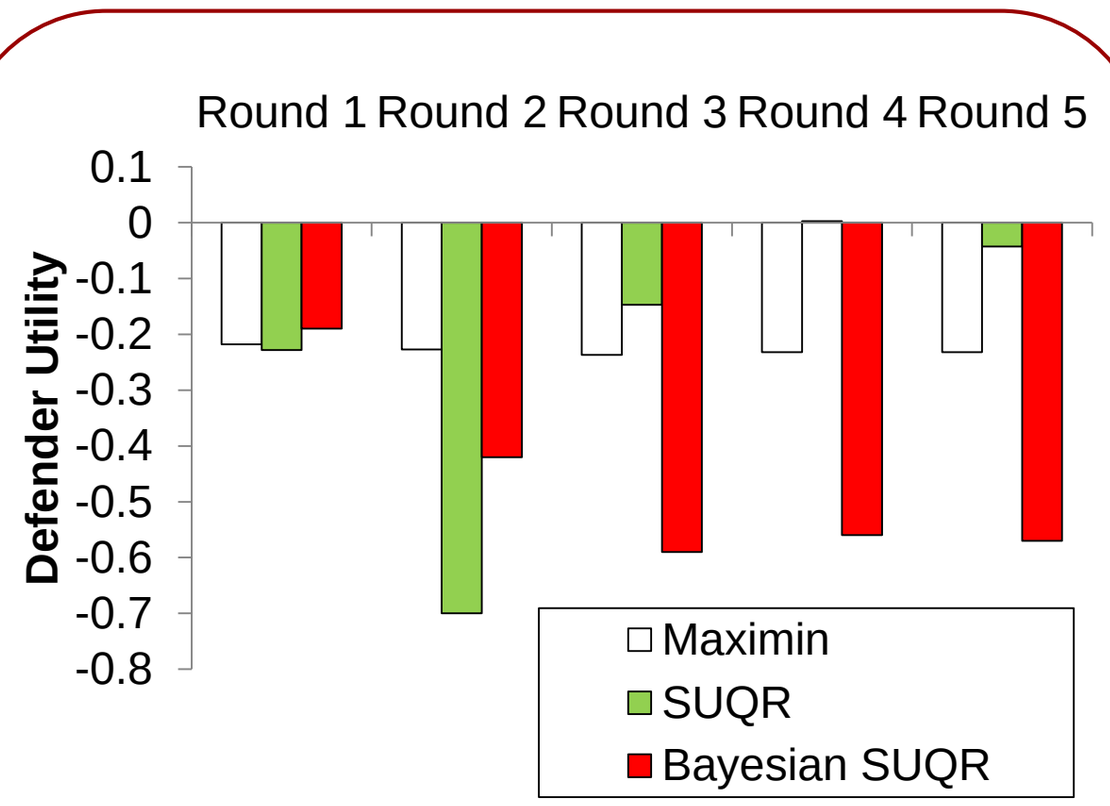
$$\text{Adversary's probability of choosing target j} = \frac{e^{SEU^{adversary}(x,j)}}{\sum_{j'=1}^{M} e^{SEU^{adversary}(x,j')}}$$

Testing SUQR: From One-Shot to Repeated Games [2015]


Kar

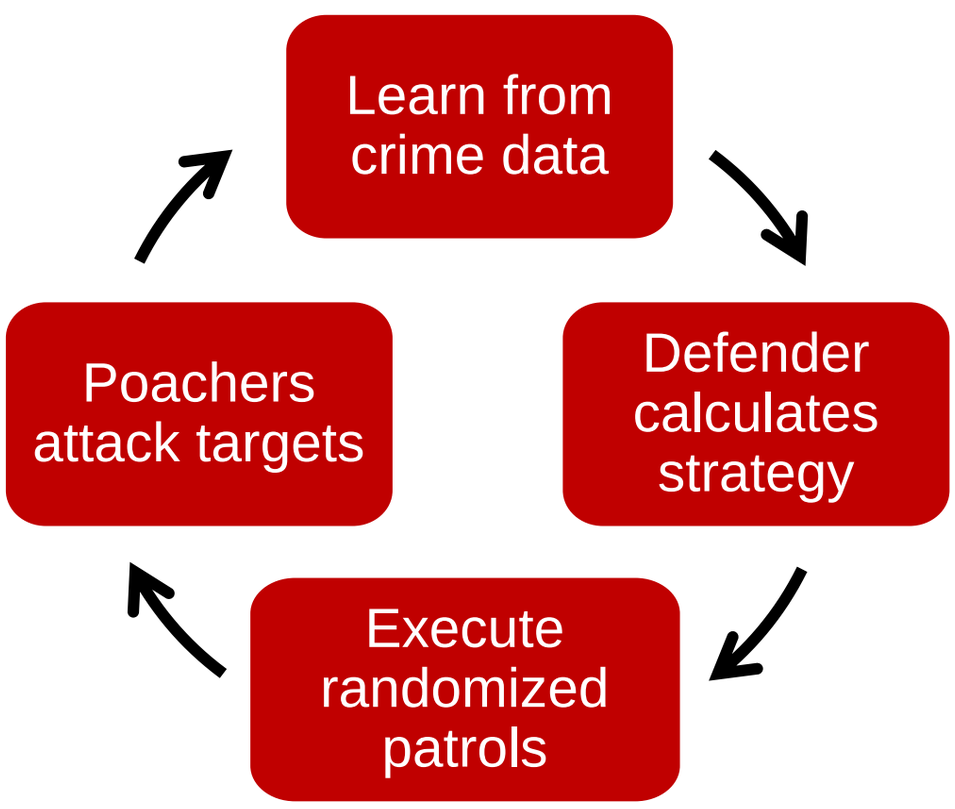


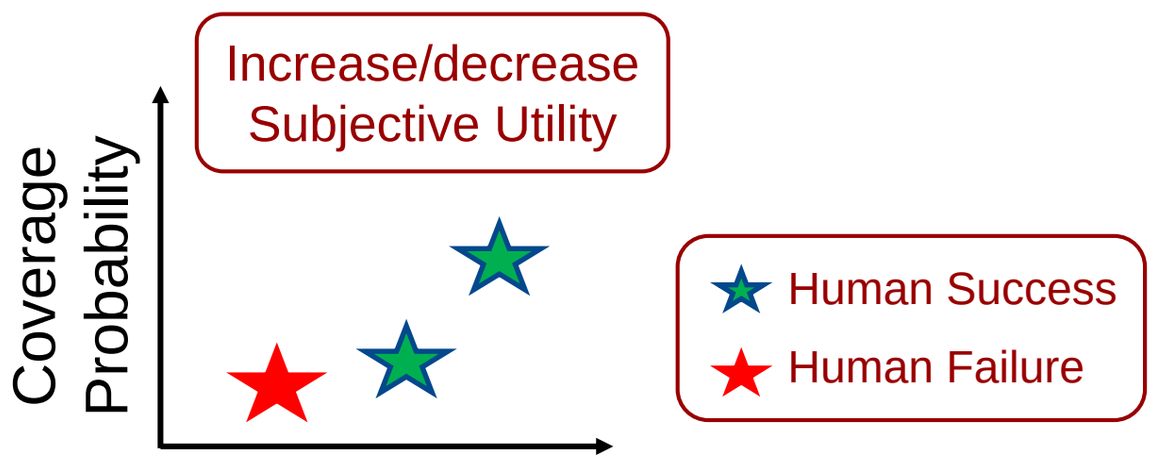
Repeated games on AMT:
35 weeks, 40 human subjects
10,000 emails!

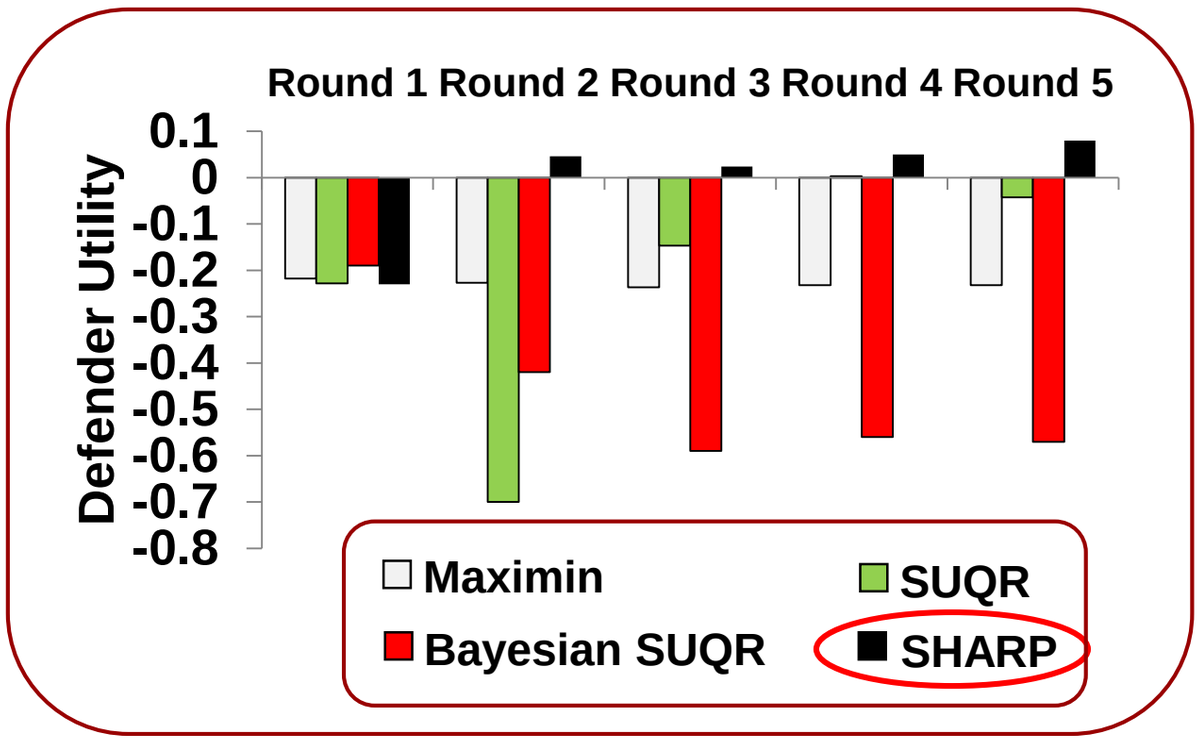



Kar

Incorporate Past Success/Failure in SUQR



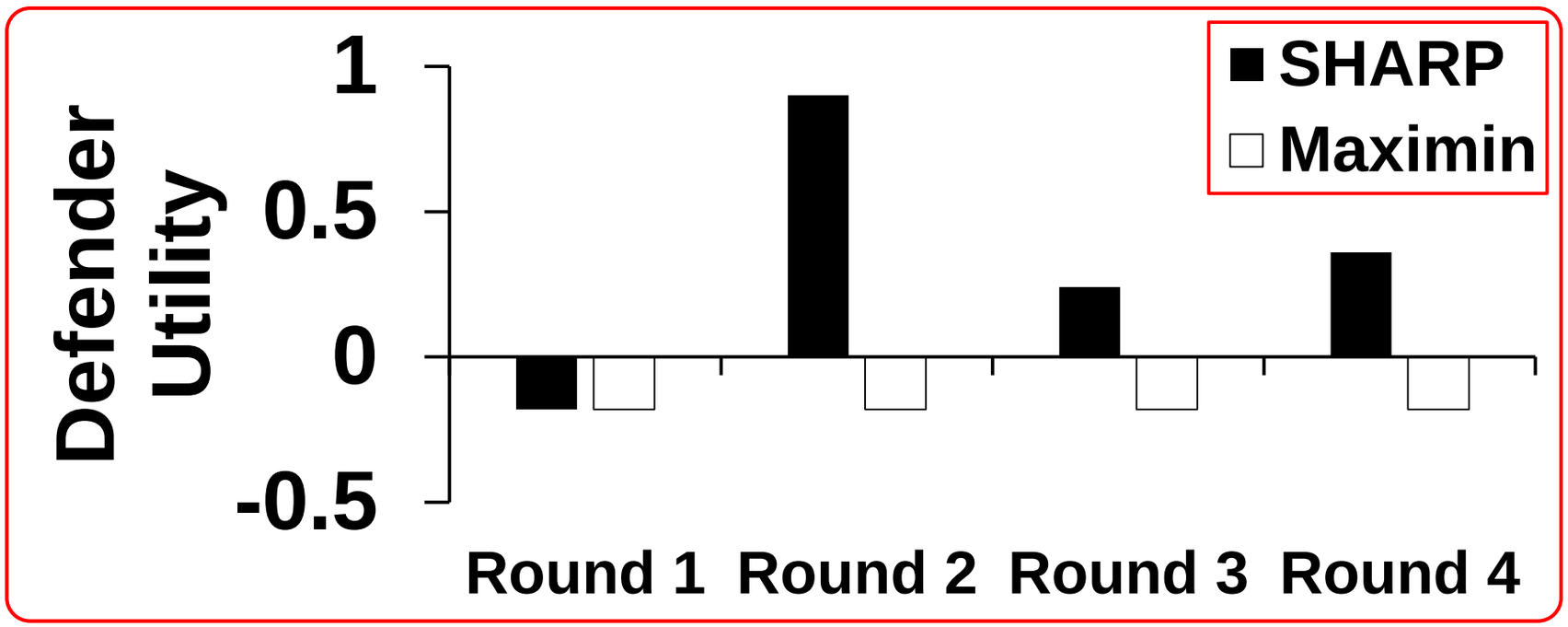




LESSON 3: SHARP AND REPEATED STACKELBERG GAMES


Kar

Performance against Rangers in Indonesia



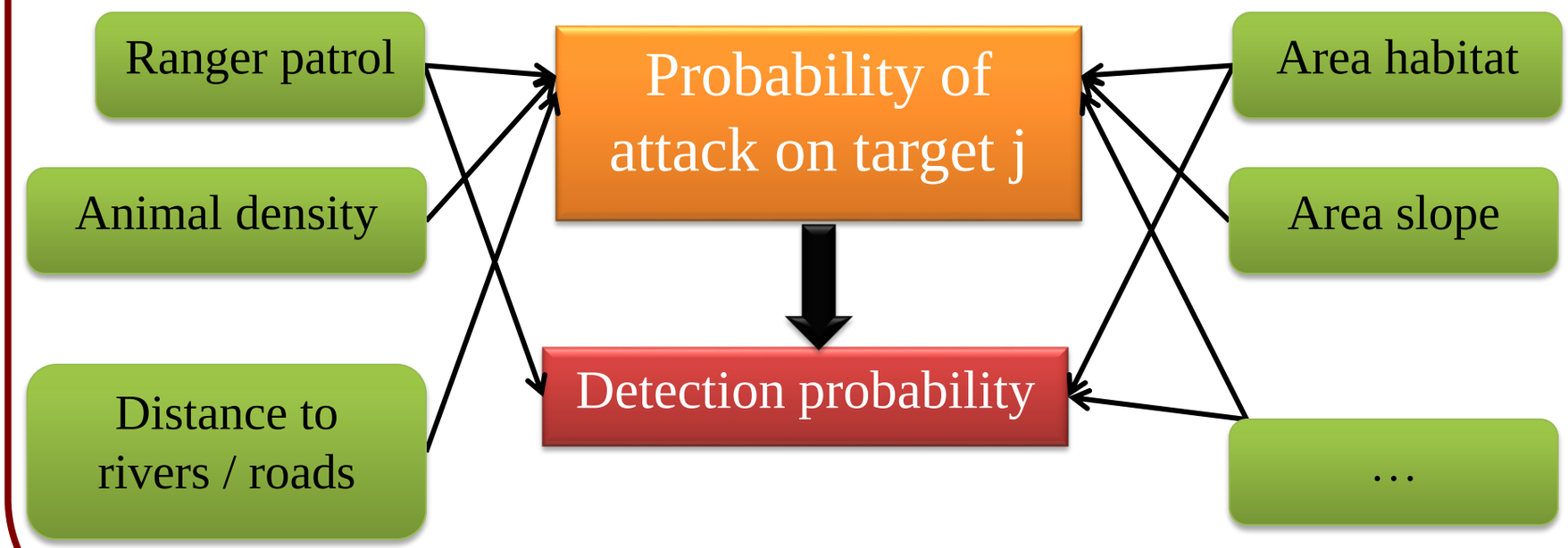
PAWS: PROTECTION ASSISTANT FOR WILDLIFE SECURITY

Nguyen

Queen Elizabeth National Park, Uganda

SUQR model, 12 years of patrols, 125000 observations

$$\propto e^{(\boldsymbol{w1} \times CaptureProb + \boldsymbol{w2} \times Feature_1 + \boldsymbol{w3} \times Feature\_2 \ldots)}$$



PAWS: PROTECTION ASSISTANT FOR WILDLIFE SECURITY

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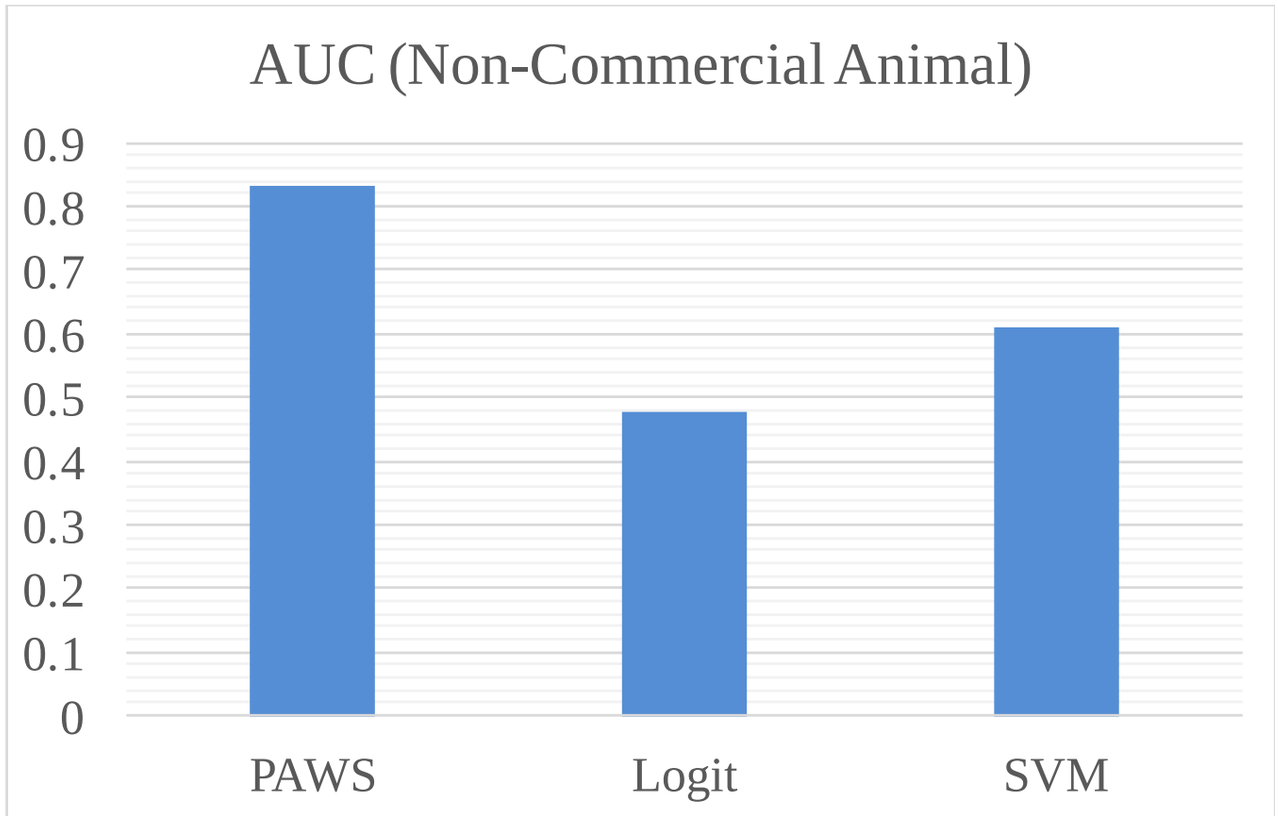
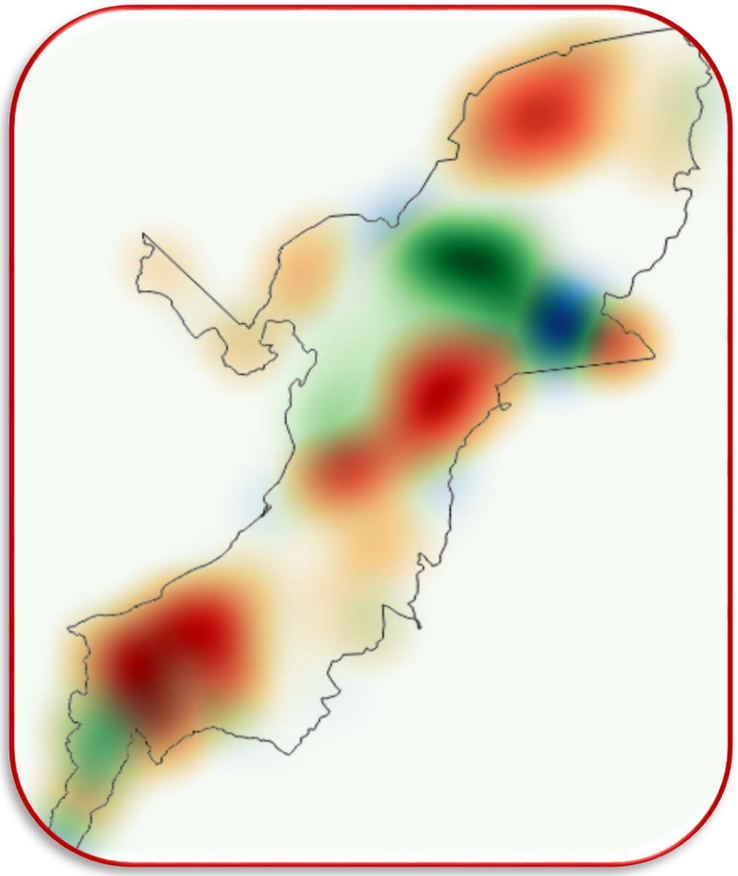


Dry Season (June-August 2008)



Green – Animal Density;

Blue – Defender Strategy;

Red – Observed Attack Probability

PAWS Patrols In The Field [2016]

Fang

Trials in Uganda and Malaysia

Important Lesson: Geography!

Uganda

Andrew Lemieux

Malaysia

Panthera

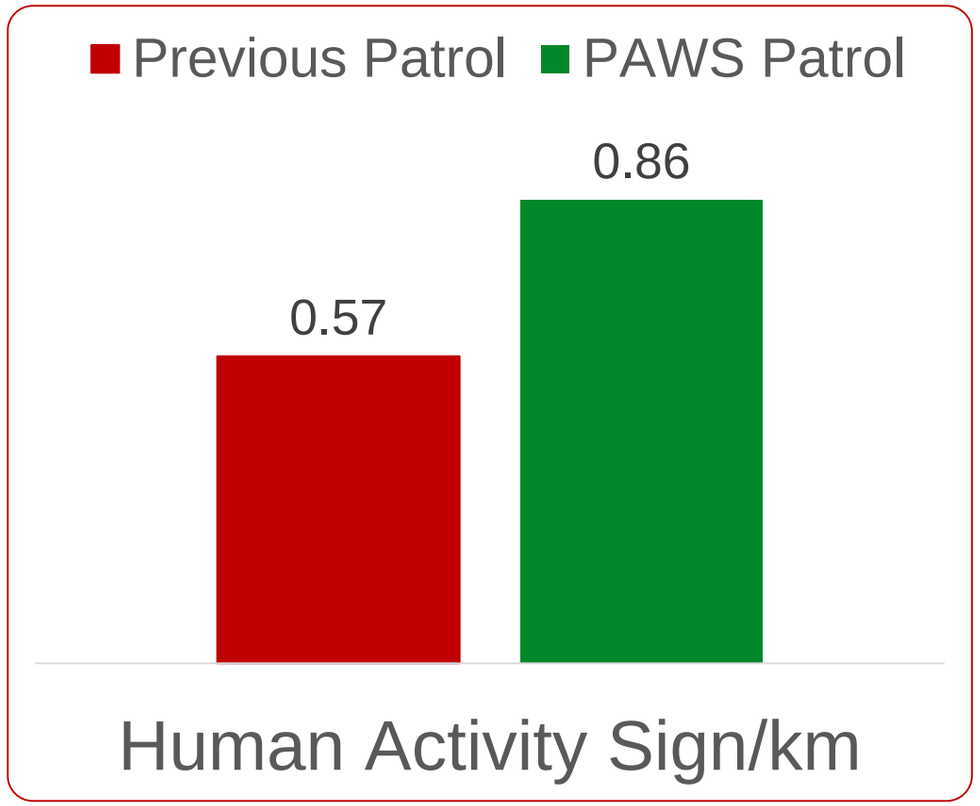
PAWS: PROTECTION ASSISTANT FOR WILDLIFE SECURITY [2016]

Path planning + Behavior Model + Species Distribution Uncertainty

PAWS: PRELIMINARY EVALUTION


Fang

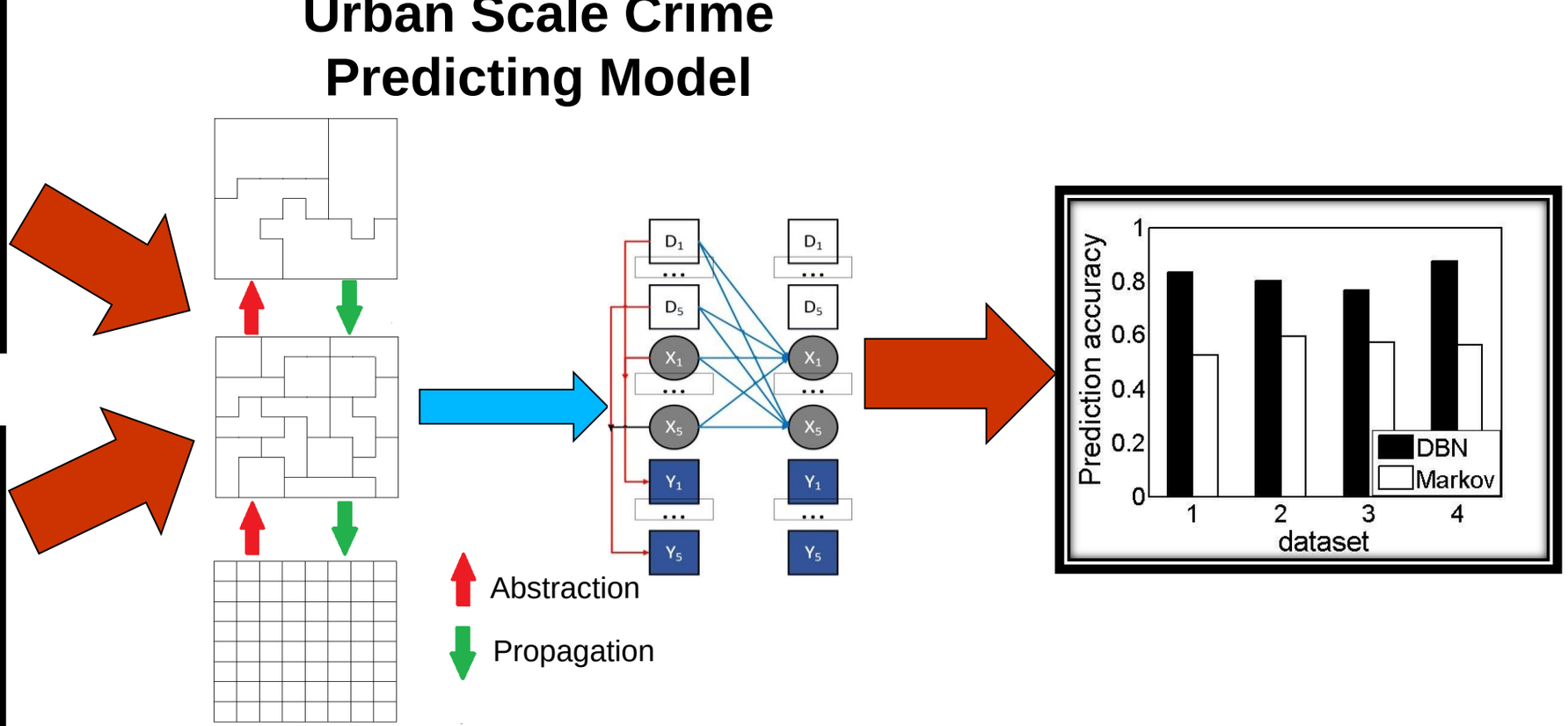
Basic Information of PAWS Patrols	
Average Trip Length	4.67 Days
Average Patrol Distance Per Day	9.29 km

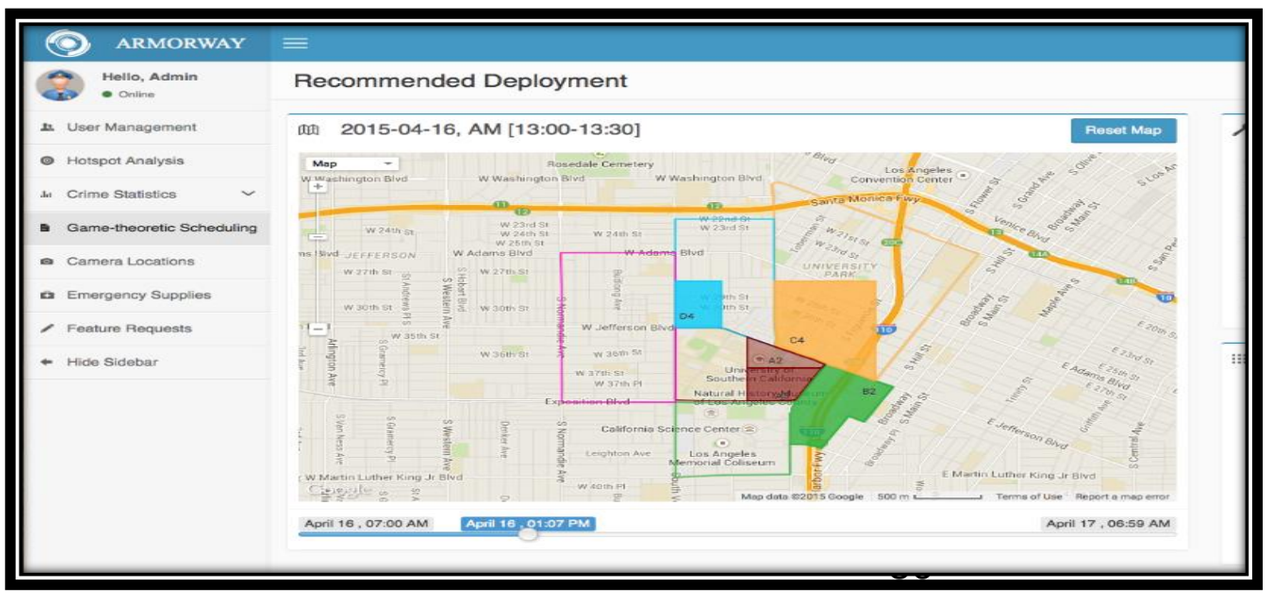


Abstract Opportunistic Crime Security Game[2016] Integrating Learning in Basic Security Game Model


Zhang Sinha

- Crime prediction: use past crime & police allocation data





EVALUATING DEPLOYED SECURITY SYSTEMS NOT EASY

How Well Optimized Use of Limited Security Resources?

Security Games superior
vs
Human Schedulers/"simple random"

Lab Evaluation	Field Evaluation: Patrol quality Unpredictable? Cover?	Field Evaluation: Tests against adversaries
Simulated adversary	Compare real schedule	"Mock attackers"
Human subject adversaries	Scheduling competition	Capture rates of real adversaries
	Expert evaluation	

WHY DOES GAME THEORY PERFORM BETTER?

Weaknesses of Previous Methods

Human Schedulers

Predictable patterns, e.g., US Coast Guard

Scheduling efforts and cognitive burden

Simple random (e.g., dice roll):

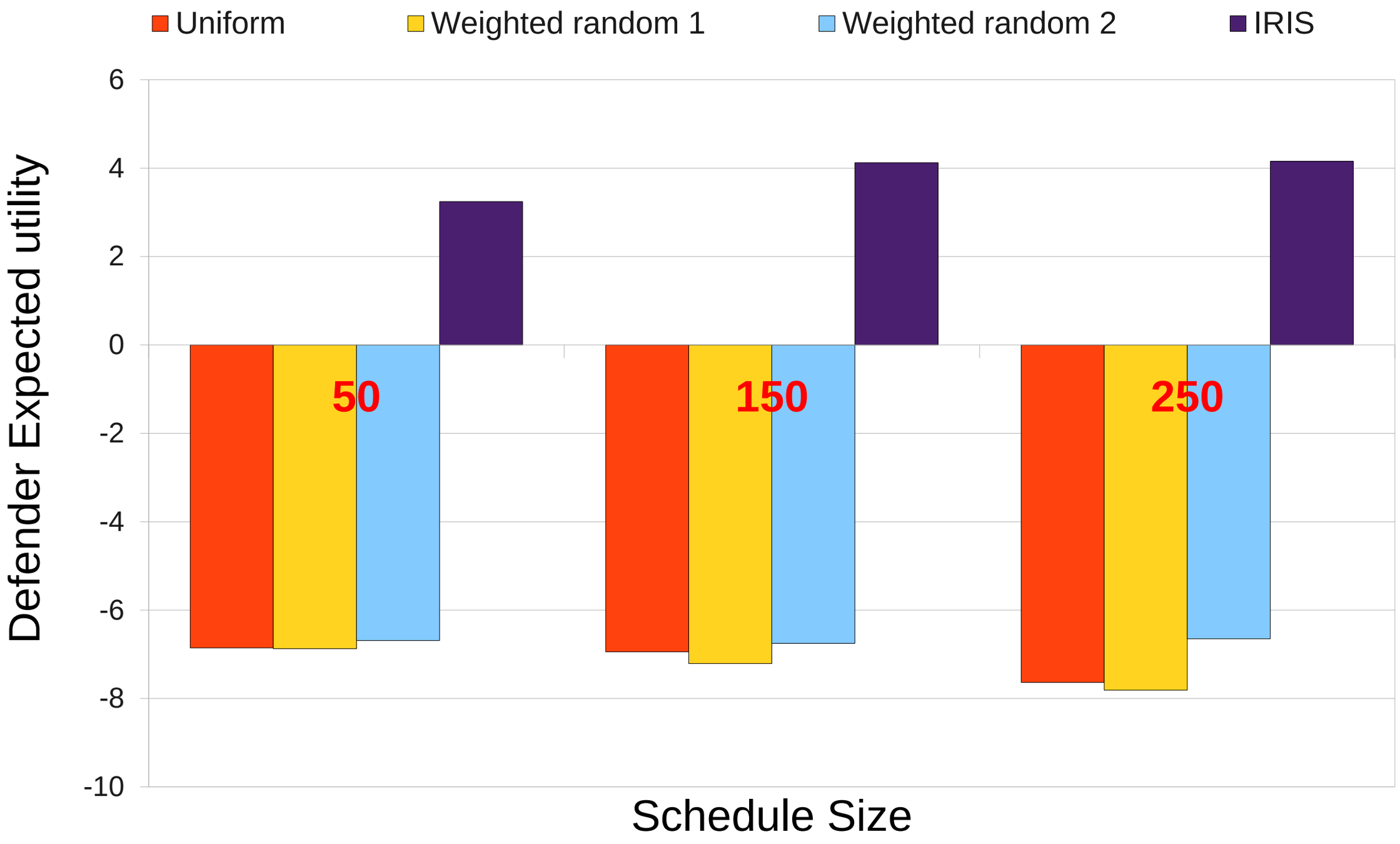
Repeatedly fails in deployments, e.g., officers to sparsely crowded terminals

Weighted random: Trillions of patrolling strategies, selecting important ones?

How to Incorporate learned adversary models, planning in these weights?

Multiple deployments over multiple years: No forced use

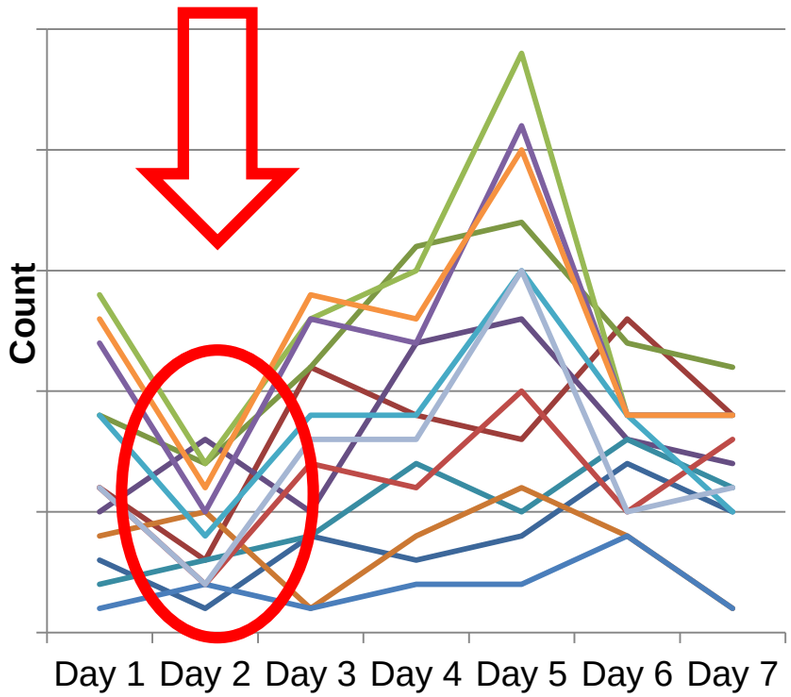
Lab Evaluation via Simulation: IRIS (FAMS)



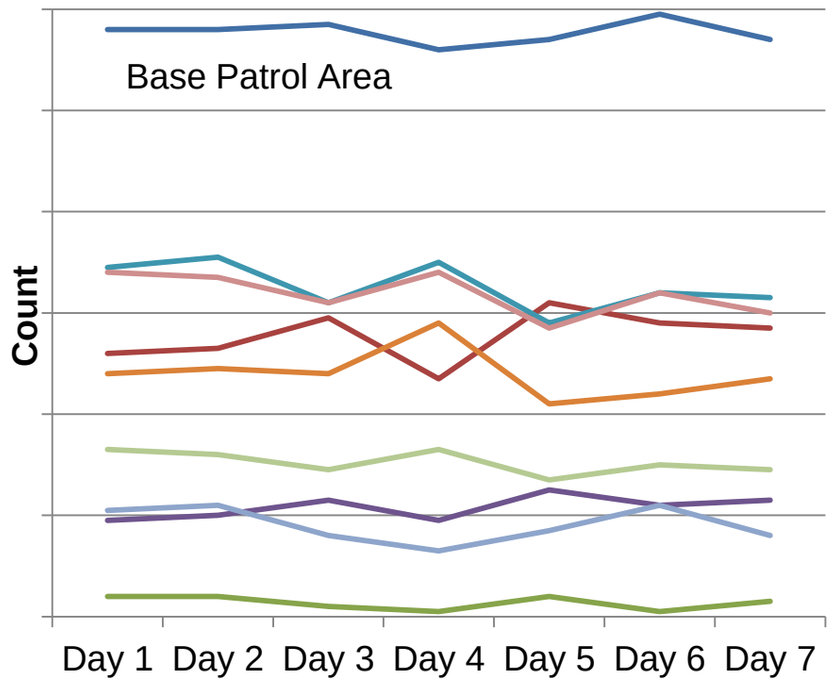
FIELD EVALUATION OF SCHEDULE QUALITY

Improved Patrol Unpredictability & Coverage for Less Effort

Patrols Before PROTECT: Boston



Patrols After PROTECT: Boston



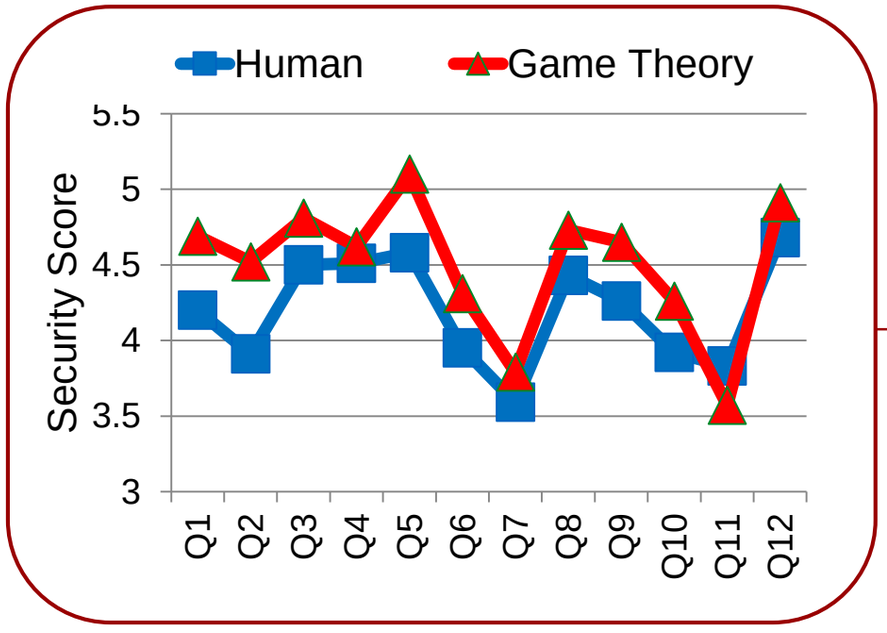
PROTECT (Coast Guard): 350% increase in defender expected utility

FIELD EVALUATION OF SCHEDULE QUALITY

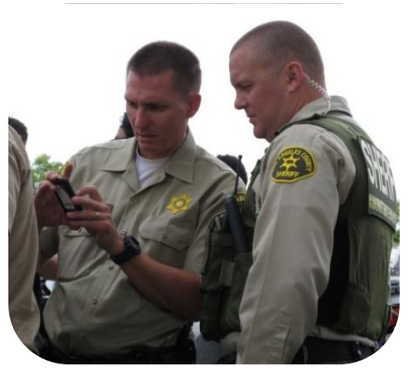
Improved Patrol Unpredictability & Coverage for Less Effort

FAMS: IRIS Outperformed expert human over six months

Report:GAO-09-903T



Trains: TRUSTS outperformed expert humans schedule 90 officers on LA trains



FIELD TEST AGAINST ADVERSARIES: MOCK ATTACKERS

Example from PROTECT

”Mock attacker” team analysis

PRE- to POST-PROTECT (Boston): “Deterrence” Improved

Additional real-world indicators from Boston:

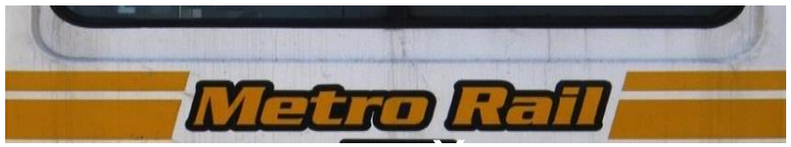
Boston boaters’ questions: “..has the Coast Guard recently acquired more boats”

POST-PROTECT: Actual reports of illegal activity

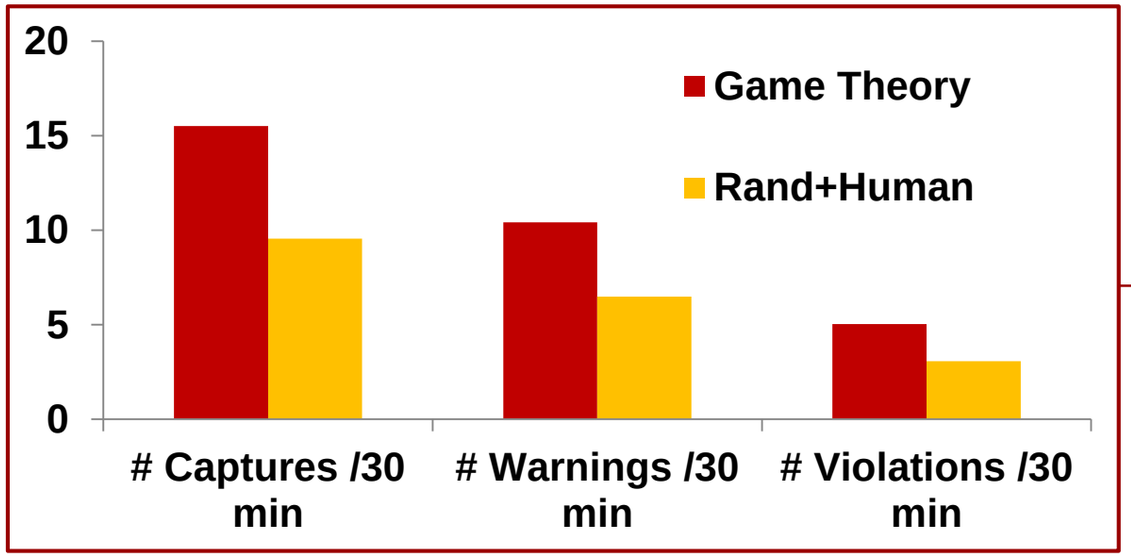
FIELD TESTS AGAINST ADVERSARIES

Computational Game Theory in the Field

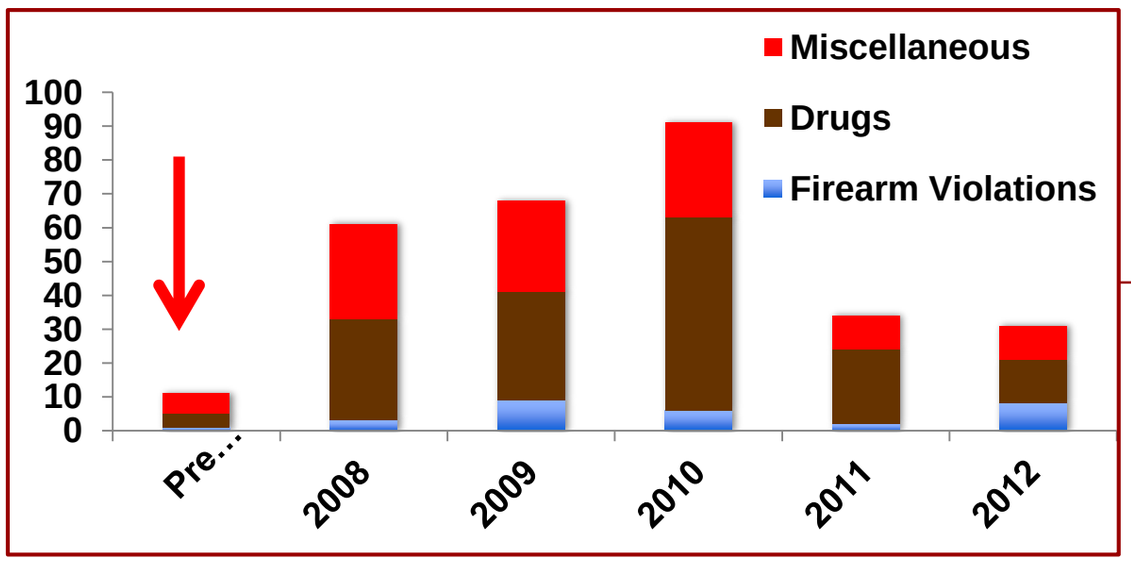
Controlled



- Game theory vs Random
- 21 days of patrol
- Identical conditions
- Random + Human



Not Controlled



EXPERT EVALUATION

Example from ARMOR, IRIS AND PROTECT

June 2013: Meritorious Team Commendation from Commandant (US Coast Guard)

July 2011: Operational Excellence Award (US Coast Guard, Boston)

Transportation Security Administration

Office of Law Enforcement/Federal Air Marshal Service

Milind Tambe

In recognition and appreciation of your outstanding achievement in developing the Intelligent Randomization In Scheduling (IRIS) program to advance the mission of the Office of Law Enforcement/Federal Air Marshal Service.

This 2nd day of September, 2011

James B. Curren
Studies, Research and Analysis
Office of Flight Operations

September 2011: Certificate of Appreciation (Federal Air Marshals)

February 2009: Commendations LAX Police (City of Los Angeles)

KEY LESSONS: SECURITY GAMES

Decision aids based on computational game theory in daily use

Optimize limited security resources against adversaries

Application yield research challenges: Key advances in security games

Scale-up: Incremental strategy generation & Marginals

Uncertainty: Integrate MDPs, Robustness

Human Behavior: Model innovations based on quantal response

Current applications: Global, interdisciplinary challenges

Green security games: criminology, computation, conservation

GLOBAL EFFORTS ON SECURITY GAMES: YET JUST THE BEGINNING…

Thank you to sponsors:

CREATE HOMELAND SECURITY CENTER

Transportation Security Administration

Army Research Office

THANK YOU

tambe@usc.edu

http://teamcore.usc.edu/security

TRANSPORTATION, SOCIAL NETWORK [2013]


Jain

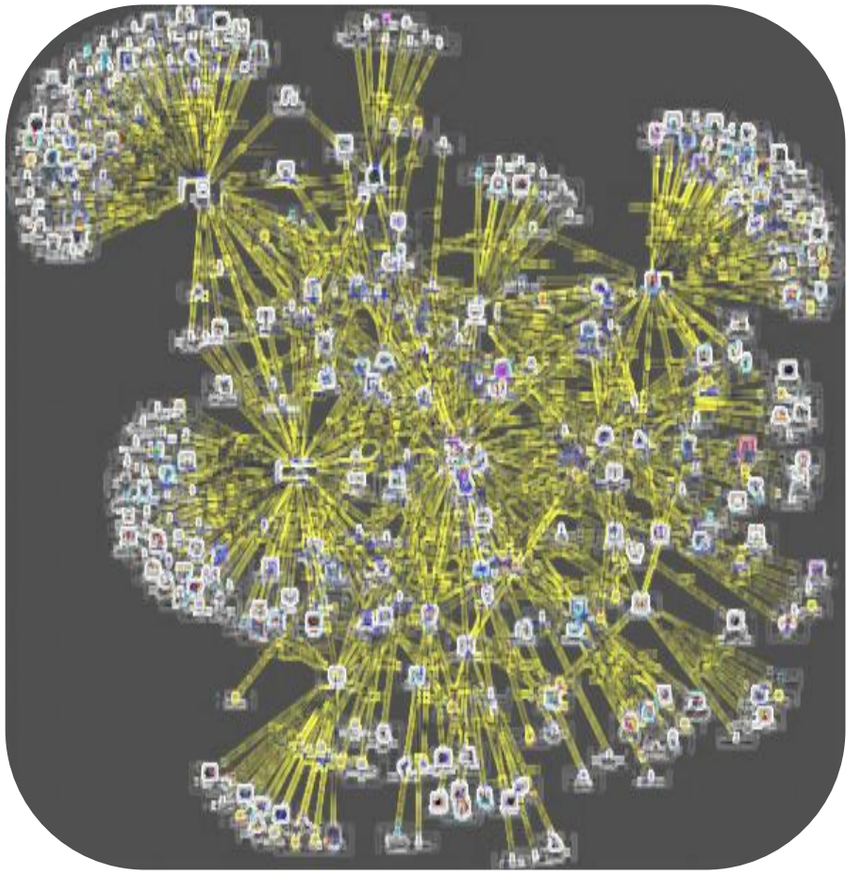
Scale-up: Incremental Strategy Generation

Road networks:

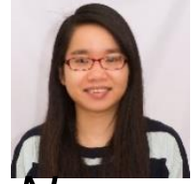
20,000 roads, 15 checkpoints
(solved under 20 min)

Social networks:

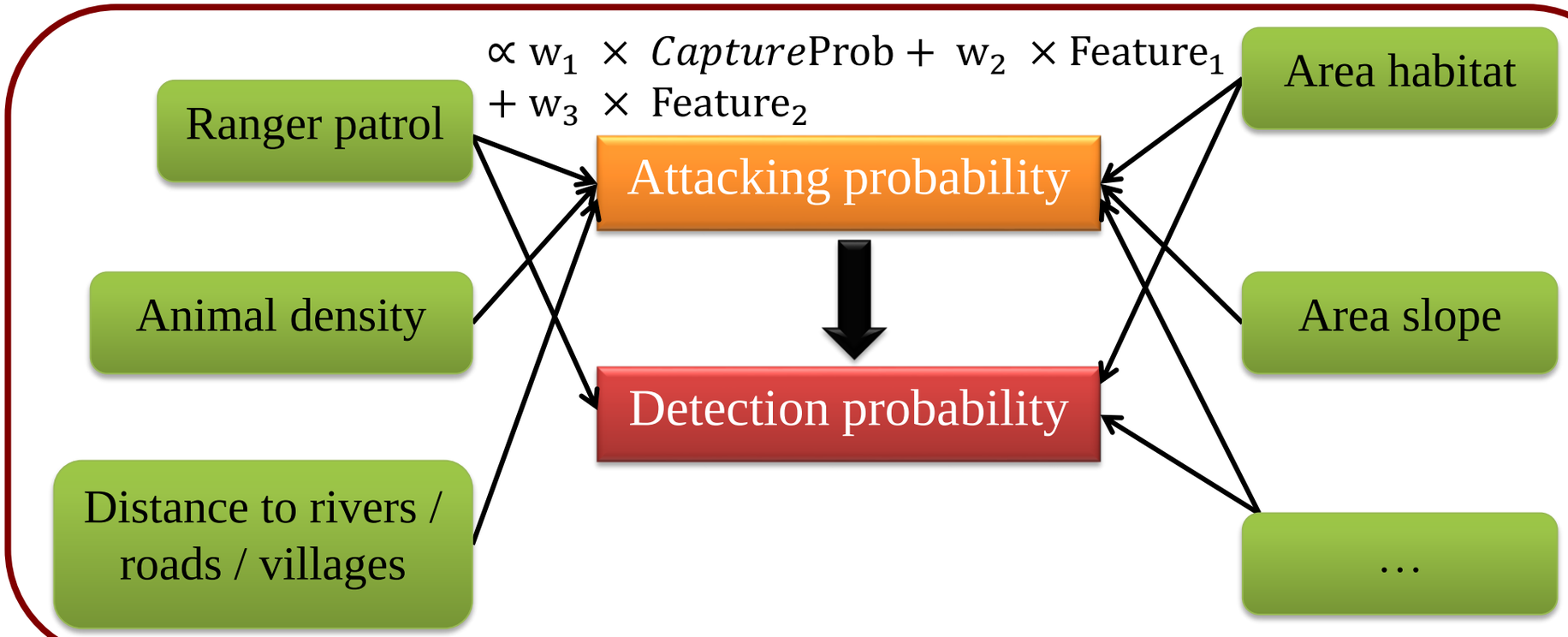
e.g., counter-insurgency



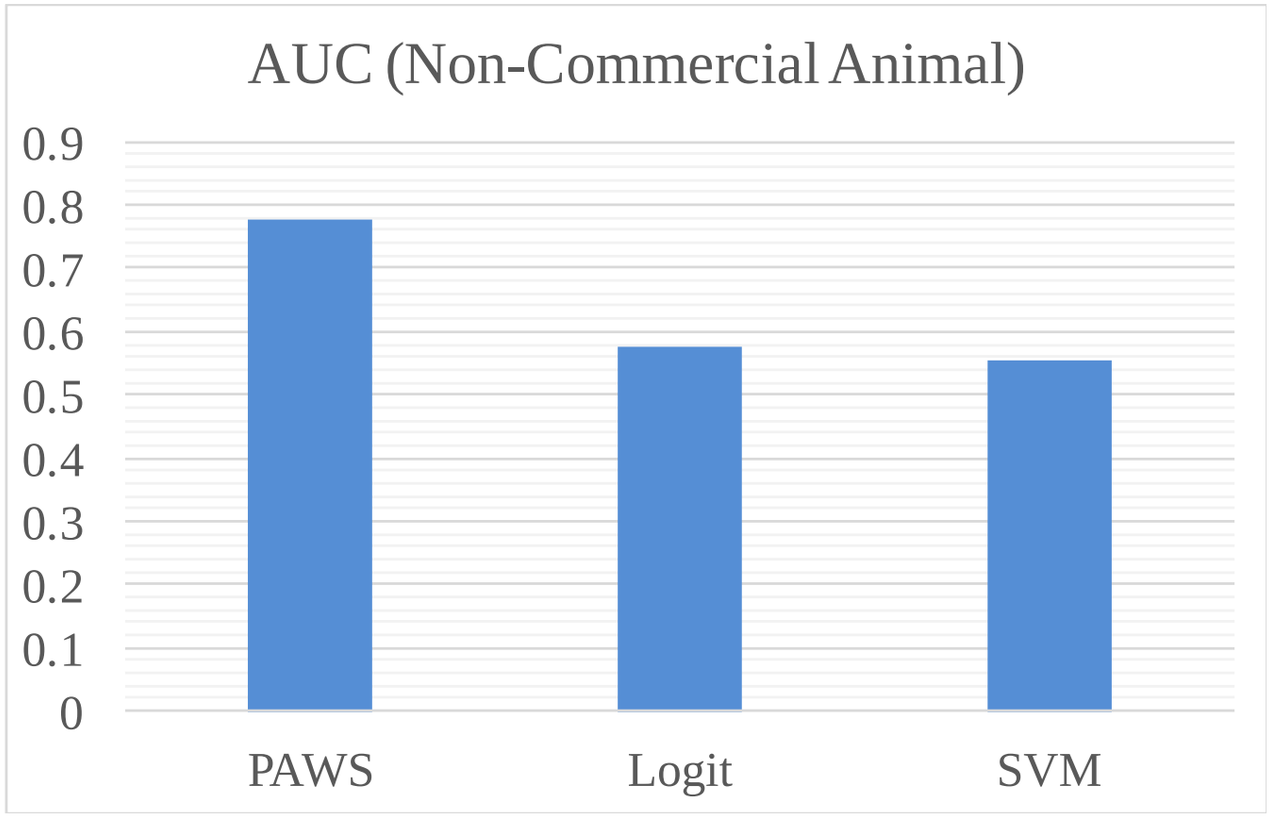
PAWS: PROTECTION ASSISTANT FOR WILDLIFE SECURITY (8 years)



Nguyen



- **QENP: ~2500 km²**
- **12-year patrols**
- **~125000 observations**
- **6 types of illegal activities**



ARMORWAY: Founded 2013


Baghdasarian


Jain


Pita

- Los Angeles Unified School District Police
- Glendale PD
- Los Angeles Sheriff's Department
- University of Southern California
- Huntington Ingalis Industries
- US Coast Guard
- RAND Corporation
- Oakland Airport