Security Games:

Key Algorithmic Principles, Deployed Systems, Research Challenges

Milind Tambe

University of Southern California

with:

Current/former PhD students/postdocs:

Bo An, Matthew Brown, Francesco Delle Fave, Fei Fang, Benjamin Ford, William Haskell, Manish Jain, Albert Jiang, Debarun Kar, Chris Kiekintveld, Rajiv Maheswaran, Janusz Marecki, Sara McCarthy, Thanh Nguyen, Praveen Paruchuri, Jonathan Pearce,James Pita, Yundi Qian, Aaron Schlenker, Eric Shieh, Jason Tsai, Pradeep Varakantham, Haifeng Xu, Amulya Yadav, Rong Yang, Zhengyu Yin, Chao Zhang

Other collaborators:

Shaddin Dughmi (USC), Richard John (USC), David Kempe (USC), Nicole Sintov (USC), Nicholas Weller (USC) ….&

Craig Boutilier (Google), Vince Conitzer (Duke), Sarit Kraus (BIU, Israel), E Lam (Panthera), Andrew Lemieux (NCSR), Arnault Lyet (WWF), Kevin Leyton-Brown (UBC), Fernando Ordonez (U Chile), M. Pechoucek (CTU, Czech R), Rob Pickles (Panthera), Andy Plumptre (WCS), Ariel Procaccia (CMU), Tuomas Sandholm (CMU), Peter Stone (UT Austin), Y. Vorobeychik (Vanderbilt), ….&

Collaborators from the US Coast Guard, Transportation Security Administration, LA Sheriff's Dept, Uganda Wildlife Authority, …&

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

Stackelberg Security Games

Security Resource Optimization: *Not 100% Security*

- Random strategy:
  - *Increase cost/uncertainty to attackers*
- Stackelberg game:
  - *Defender commits to mixed strategy*
  - *Adversary conducts surveillance; responds*
- Stackelberg Equilibrium: Optimal random?

Adversary

Defender

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

Security Games: Research & Applications
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


LAX

TSA

Argentina airport


USC


LA Sheriff

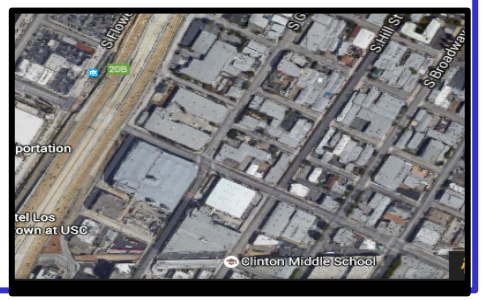
Green Security Games

Coast Guard


Panthera/WWF

IBM

Opportunistic Crime Security Games



Cyber Security Games

Global Presence of Security Games Efforts

Startup: ARMORWAY

Outline: Security Games Research (2007-)

Infrastructure Security Games

Green Security Games

Opportunistic Crime Security Games

Air travel — 2007

Ports — 2011

Trains — 2013

Fisheries — 2014

Wildlife — 2014

Urban Crime — 2015

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]

Using ARMOR as an Example


Pita Paruchuri

	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

Pr(Canine patrol, 8 AM @ Terminals 3,5,7) = 0.33

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]

Generate Mixed Strategy for Defender in ARMOR


Pita *Paruchuri*

	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	….	….	….

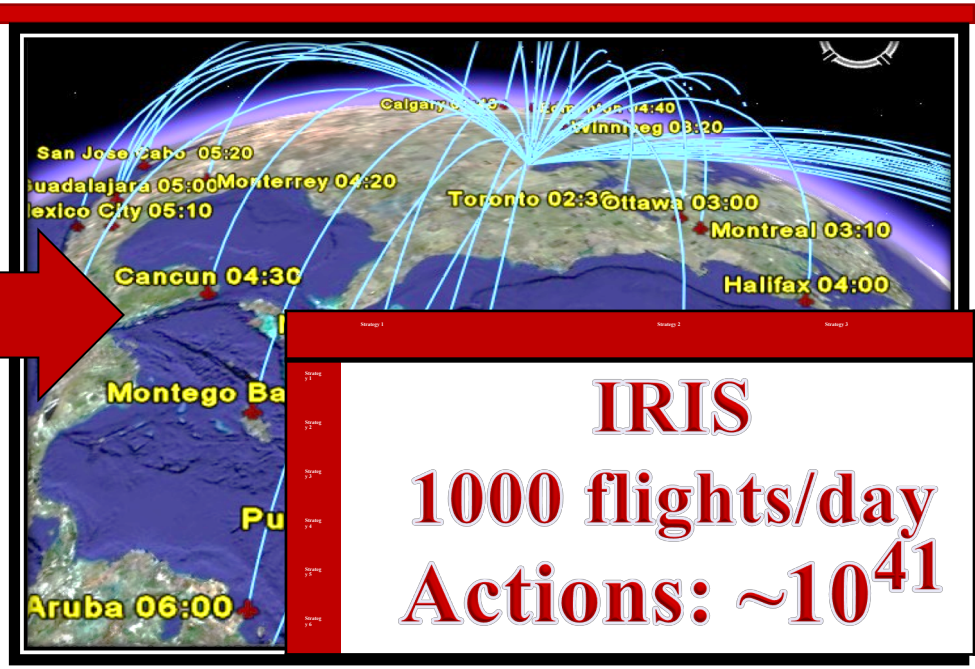
$$\max \sum_{i \in X} \sum_{j \in Q} R_{ij} \times x_i \times q_j$$

Maximize defender expected utility

+ Handling Uncertainty


Newsweek
ARMOR…throws a digital cloak of invisibility….

IRIS: Federal Air Marshals Service [2009]
Scale Up Number of Defender Strategies



- *ARMOR runs out of memory*

- *Incremental strategy generation:*
  - *Column generation: Not enumerate all 10^{41} actions*

IRIS: Incremental Strategy Generation
Column Generation


Jain Kiekintveld

Master

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

Slave

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,-10			
3,7,8	-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 University of Southern California project with* FAMS on randomizing flight schedules for the prestigious Rist Award*…"

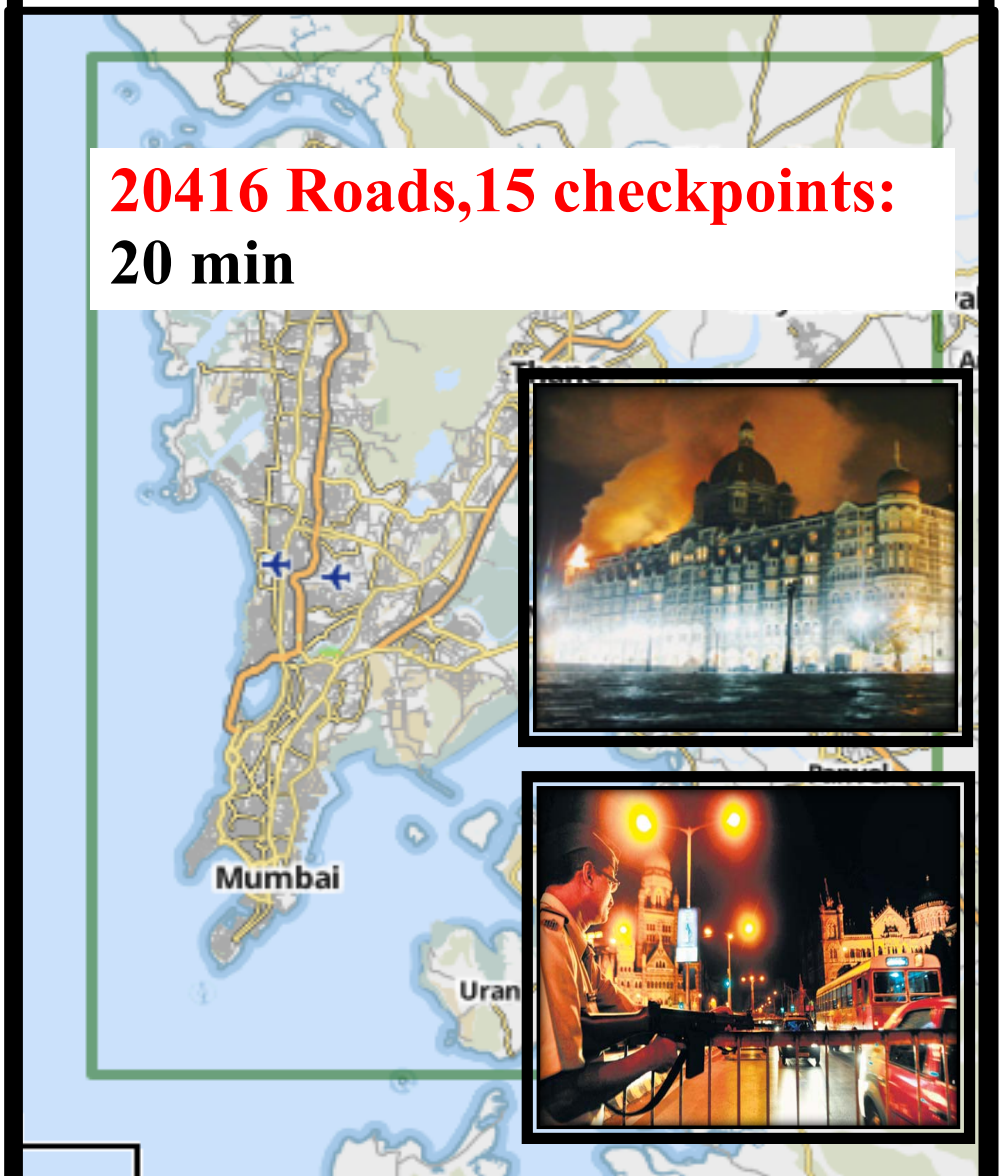
-R. S. Bray (TSA)

Transportation Security Subcommittee

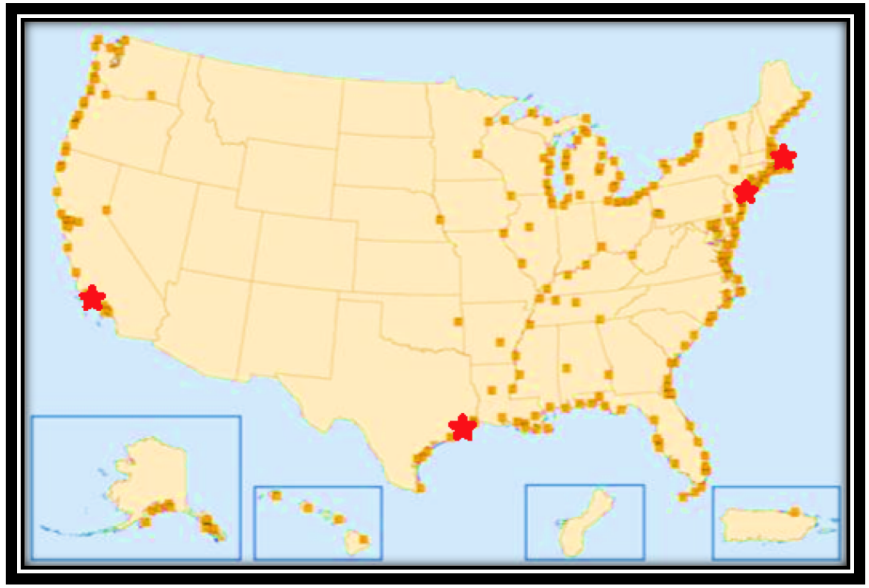
US House of Representatives 2012

Road, Social Networks[2013]
Scale-up: Double Oracle

Road networks: e.g., checkpoints



PROTECT: Port Protection Patrols Deployed 2011-
Using "Marginals" for Scale-up



USS *Cole* after attack

French oil tanker hit by small boat

PROTECT: Ferry Protection Deployed 2013-
Using "Marginals" for Scale-up

CNN iReport

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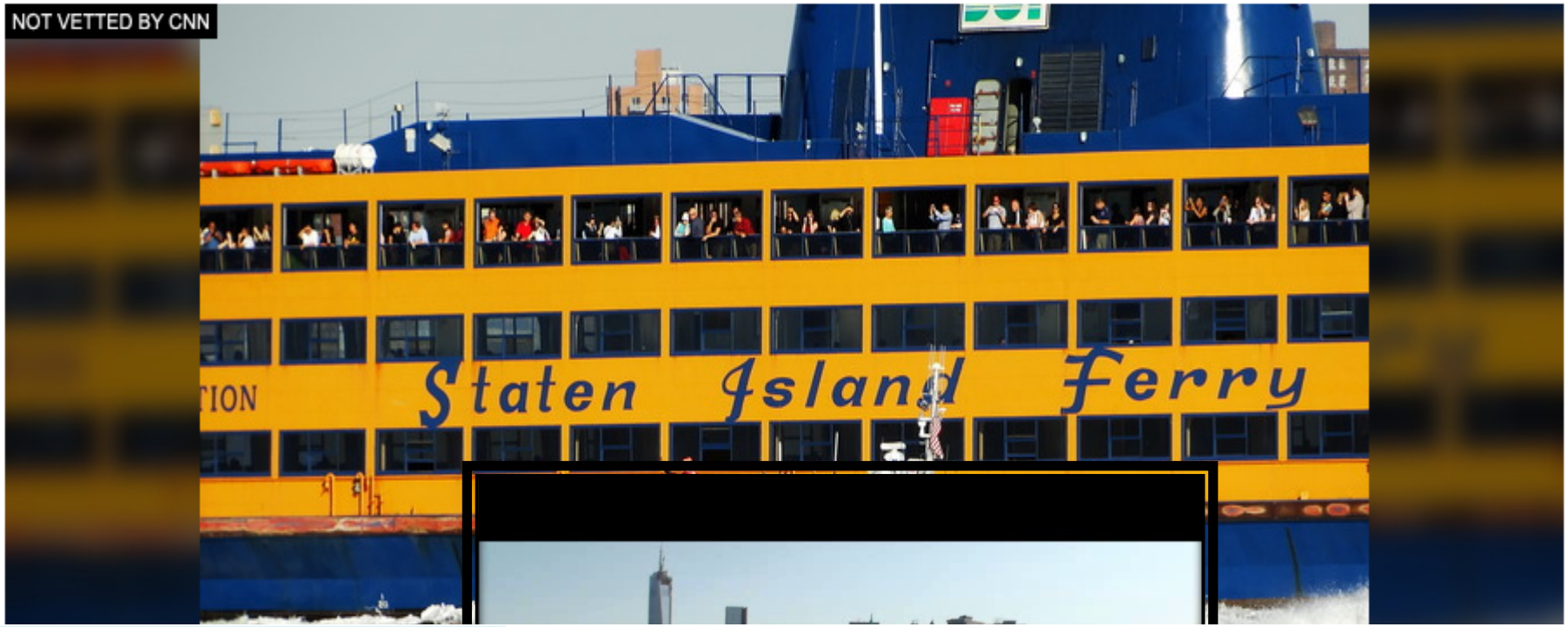

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U.S. Coast Guard protects the Staten Island Ferry | I feel safe!

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

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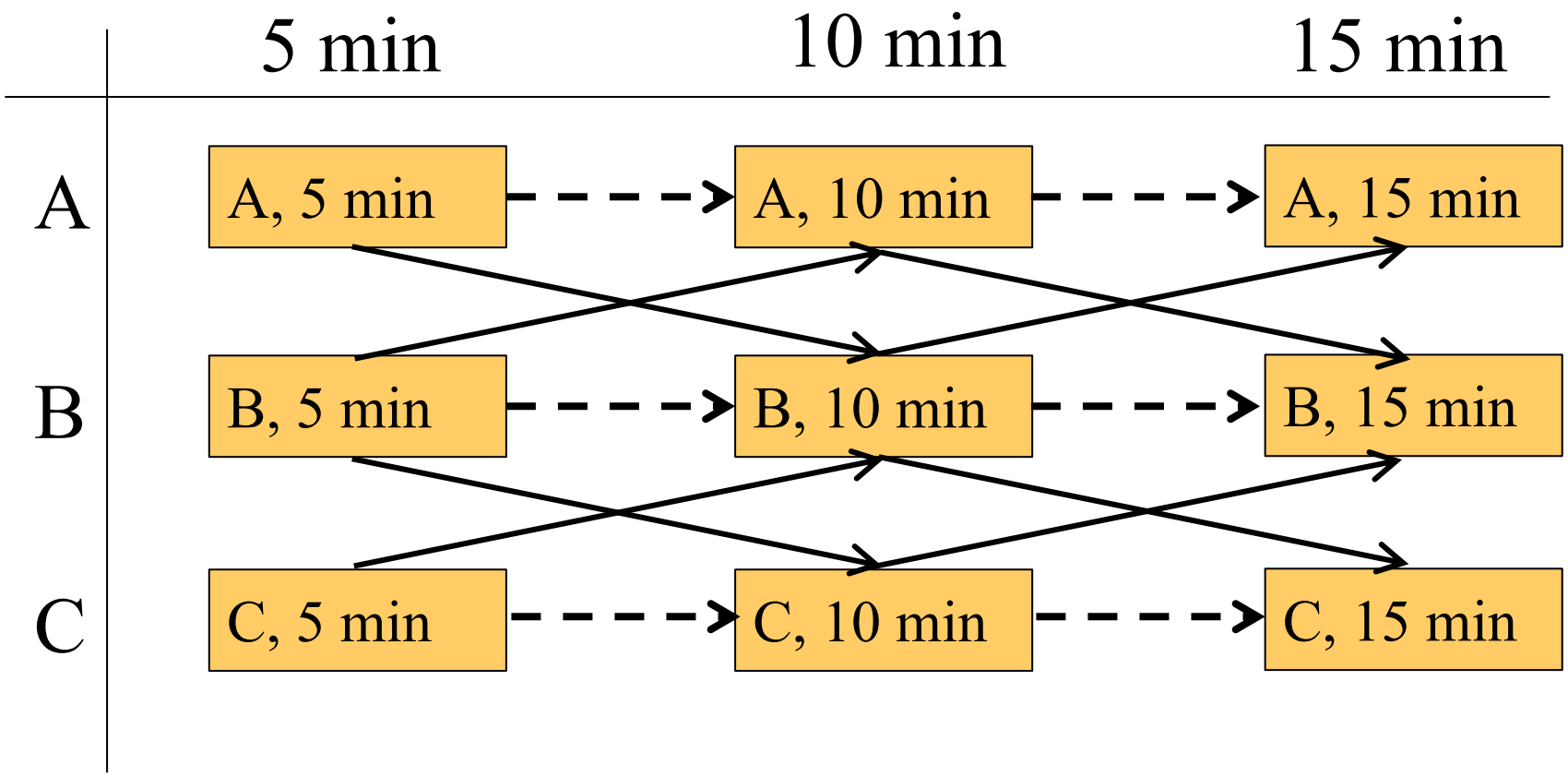
I ride the Staten Island Ferry on a daily basis to and from work. We ferry riders

Ferries: Scale-up with Mobile Resources & Moving Targets
Transition Graph Representation



Ferries: Scale-up with Mobile Resources & Moving Targets
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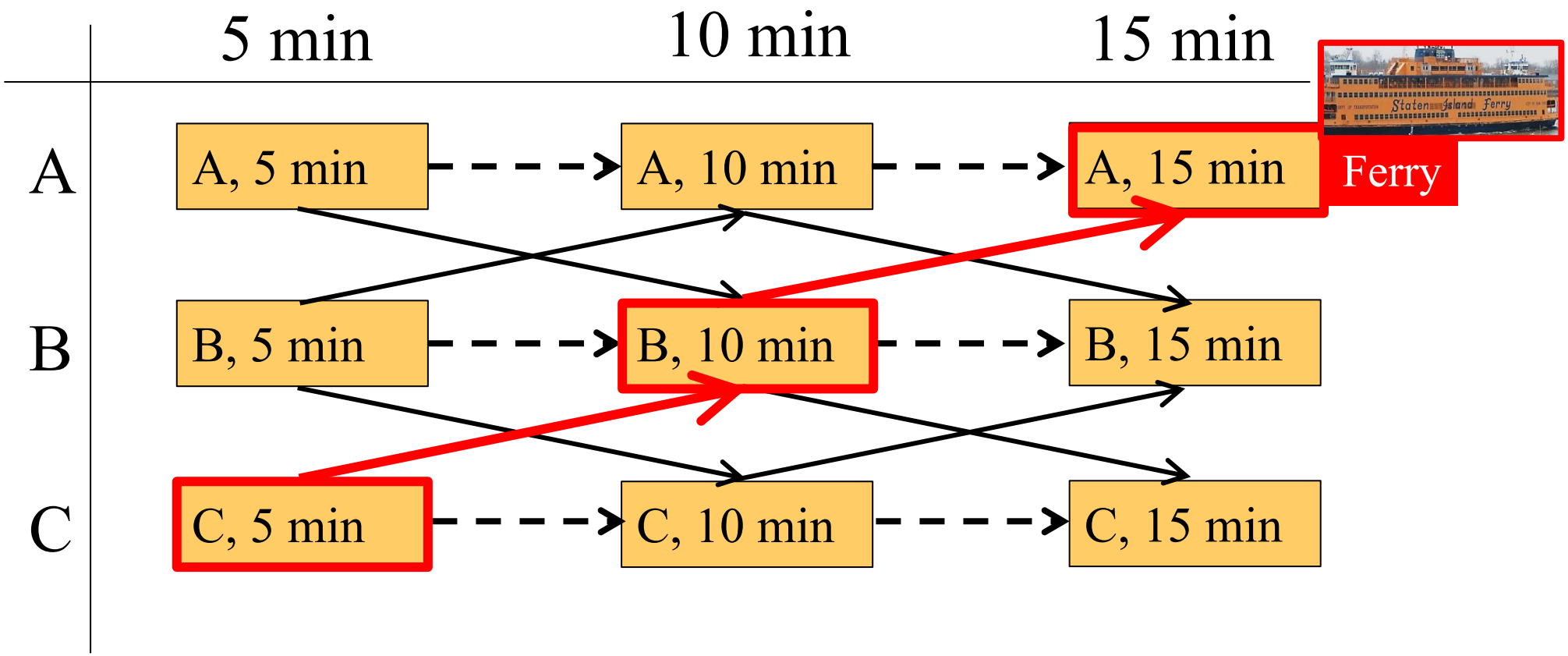
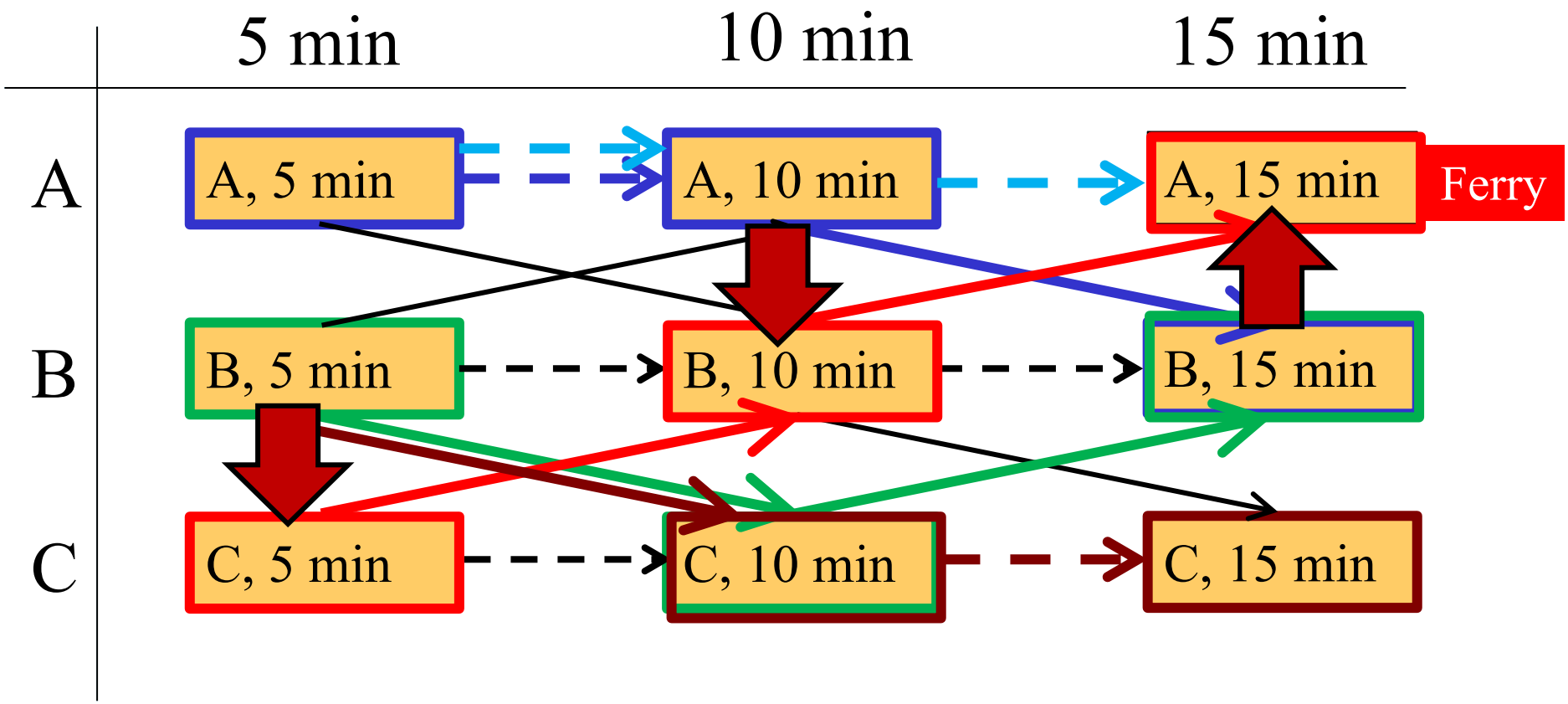


Ferries: Patrol Routes as Variables
Exponential Numbers of Patrol Routes

- Patrols protect nearby ferry location; Solve as done in ARMOR



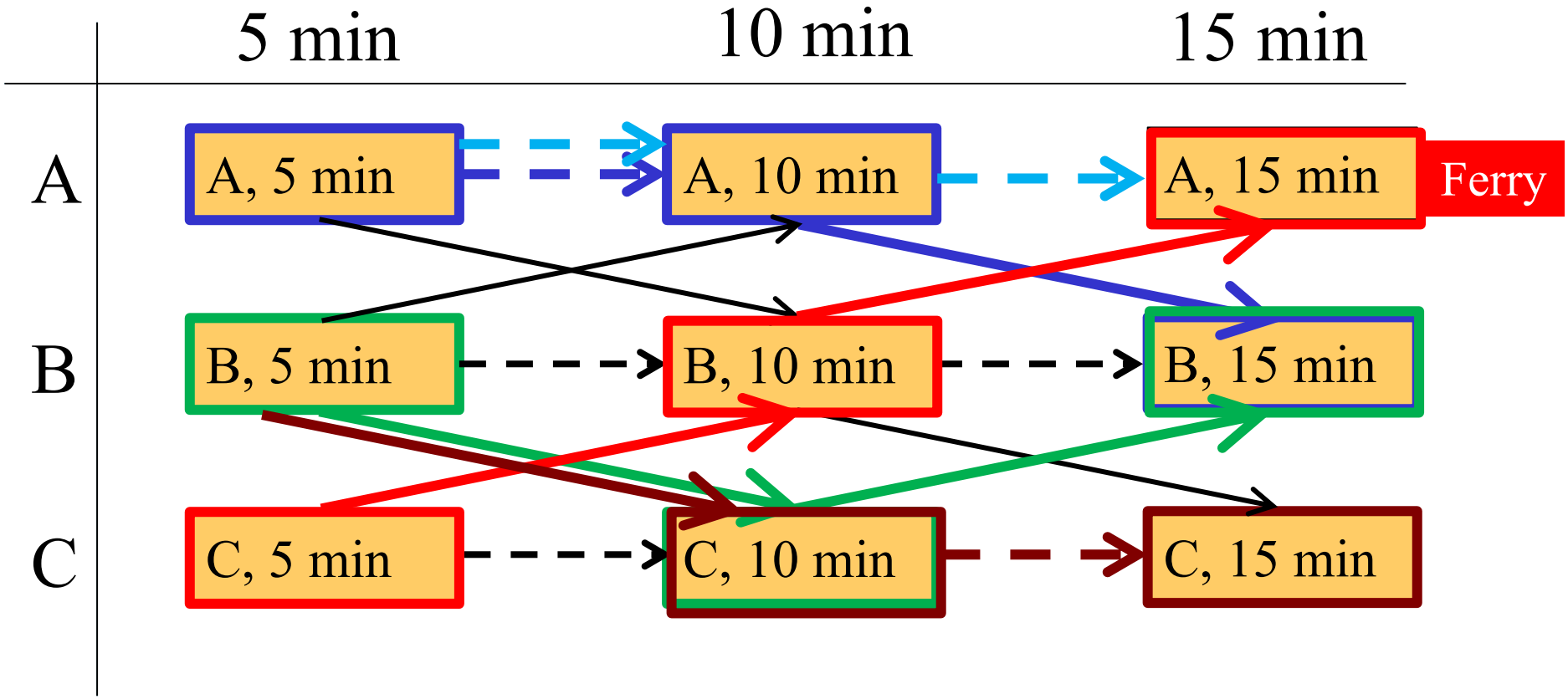
Ferries: Patrol Routes as Variables
Exponential Numbers of Patrol Routes



Fang *Jiang* *Kiekintveld*

- 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

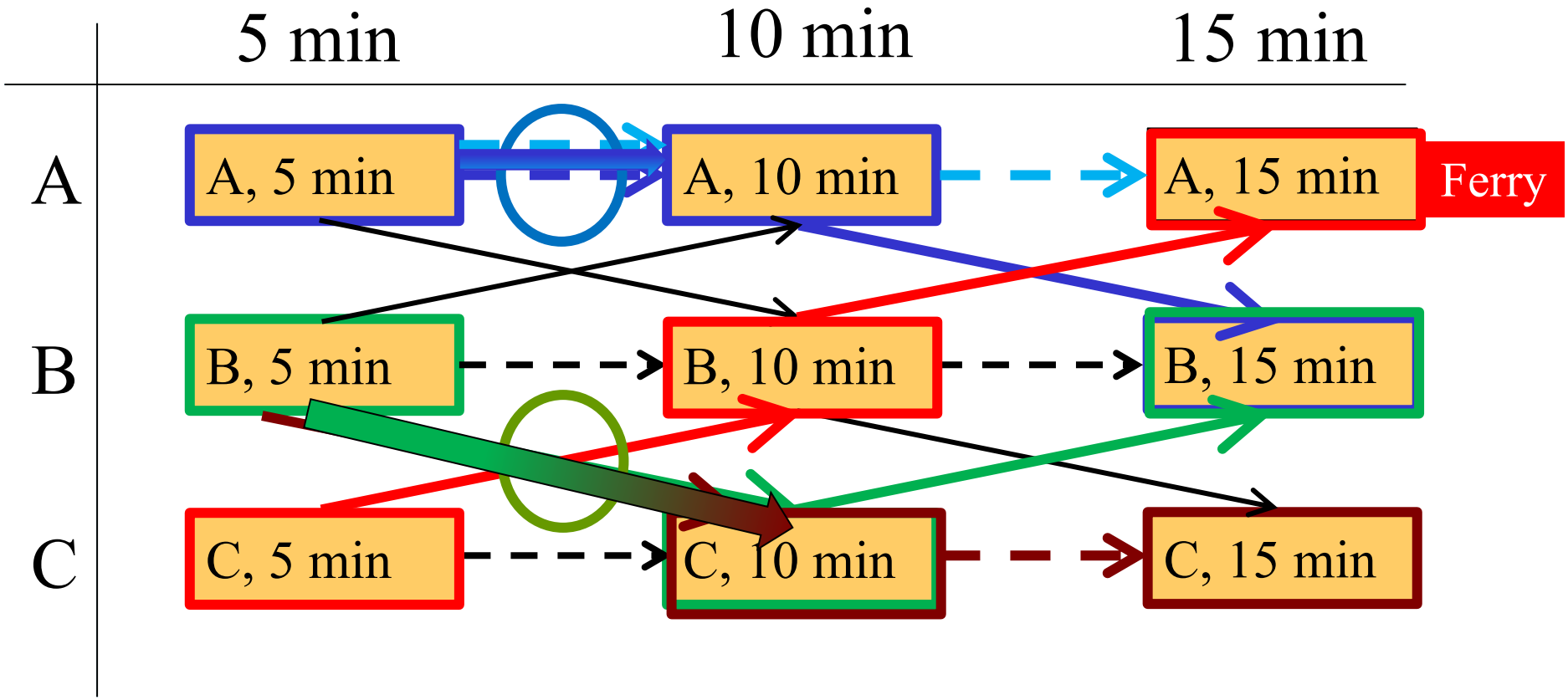


Ferries: Scale-up
Marginal Probabilities Over Segments



Fang *Jiang* *Kiekintveld*

- Variables: NOT routes, but probability flow over each segment



Ferries: Scale-up with Marginals Over Separable Segments Significant Speedup

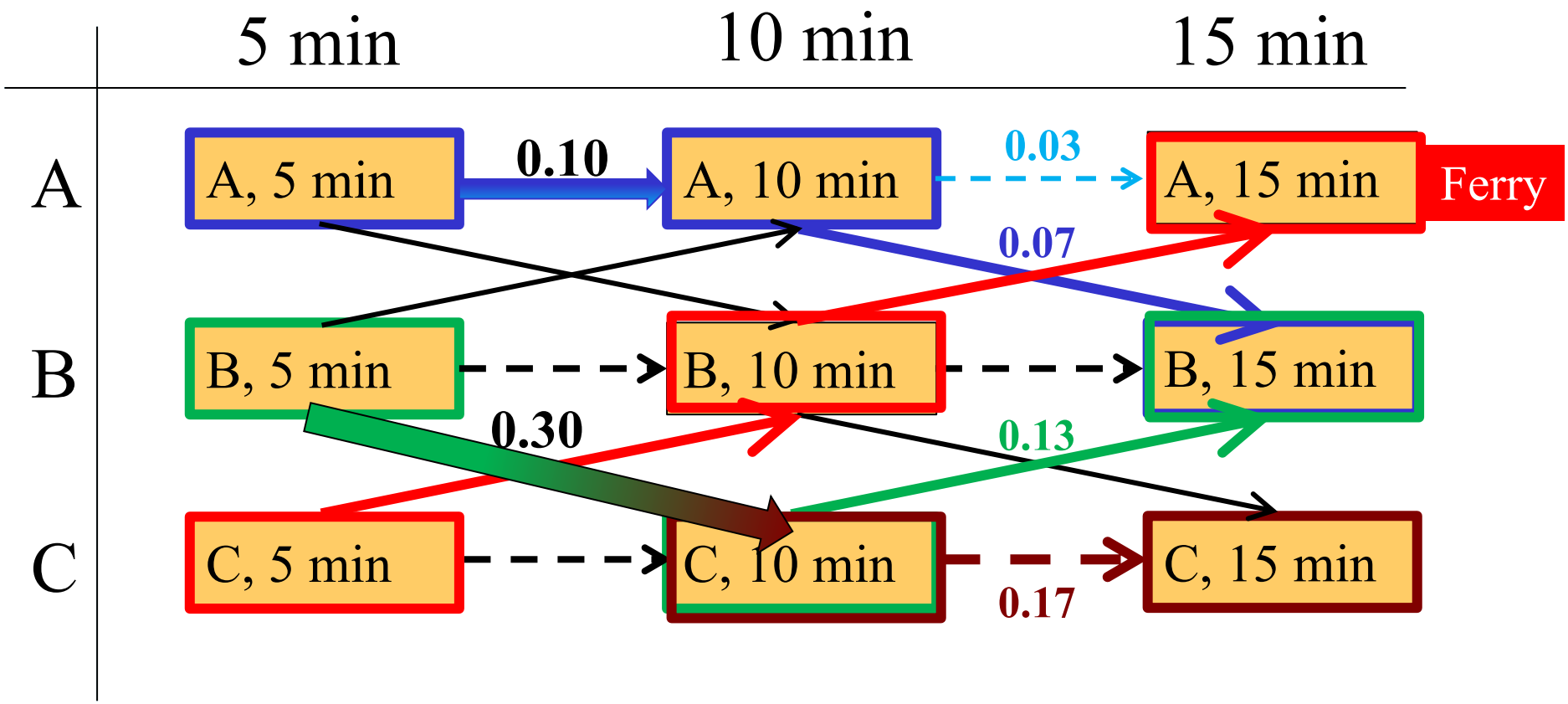
- *Obtain marginal probabilities over segments*

$N^2.T$ *variables*

N^T *variables*

Extract: [illegible](B,5), (C, 10), (C,15)]) = 0.47

[illegible](B,[illegible]), (C,10), (B,15)]) =0.23



Outline: “Security Games” Research (2007-)

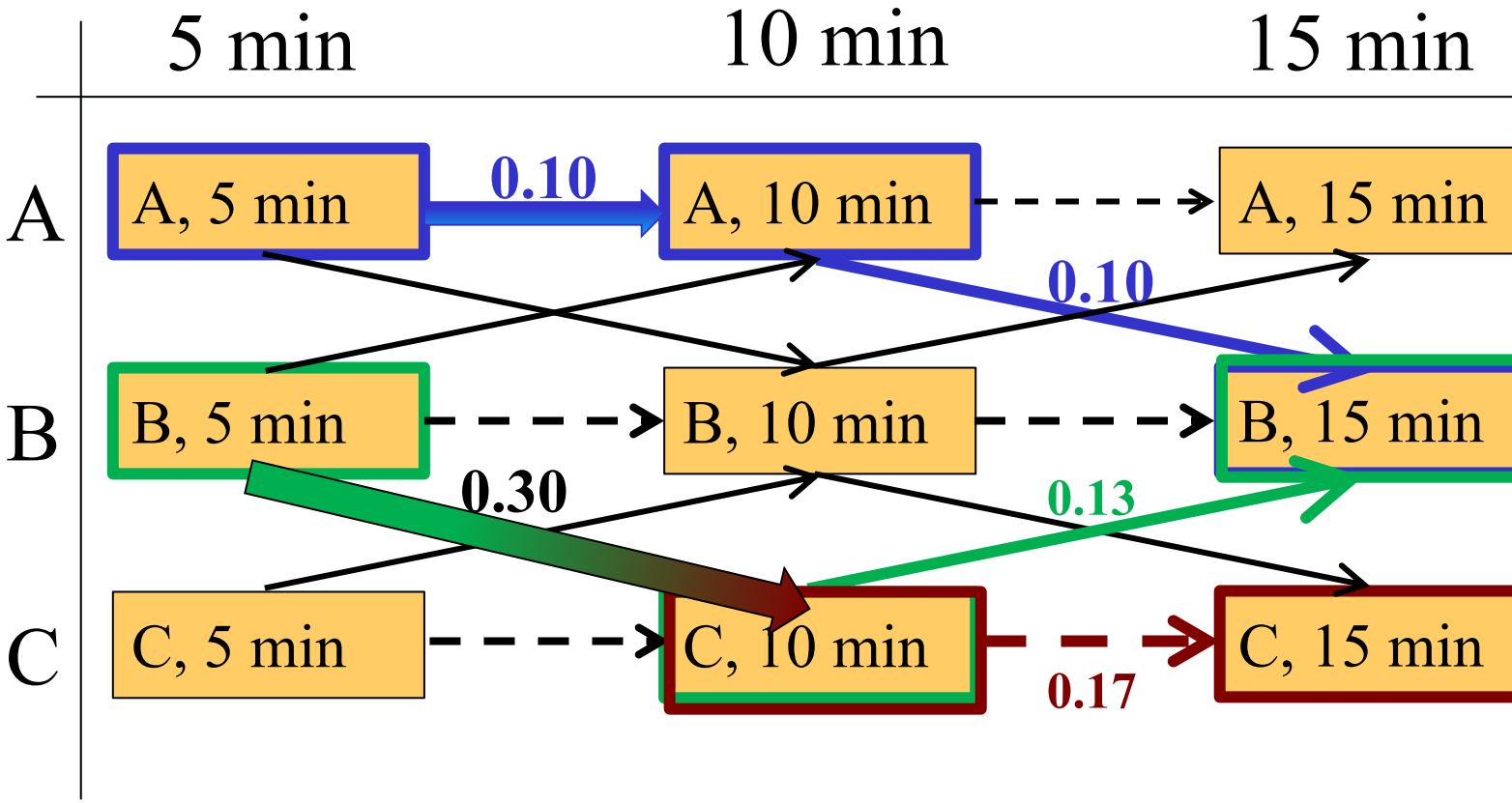
Air travel

Urban Crime

2007

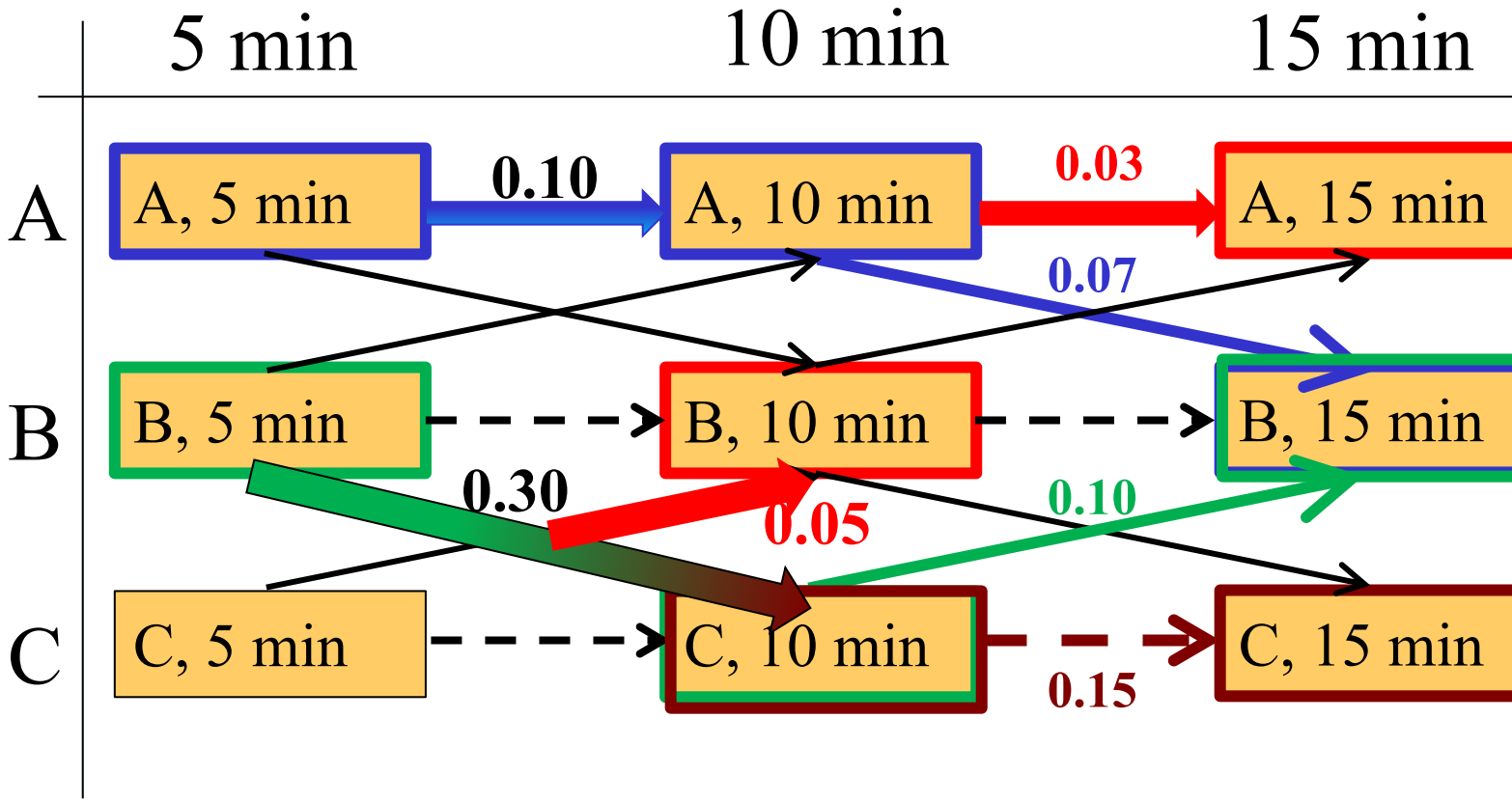
2015

TRUSTS: Frequent adversary interaction games
Patrols Against Fare Evaders



TRUSTS: Patrols Against Fare Evaders Uncertainty in Defender Action Execution

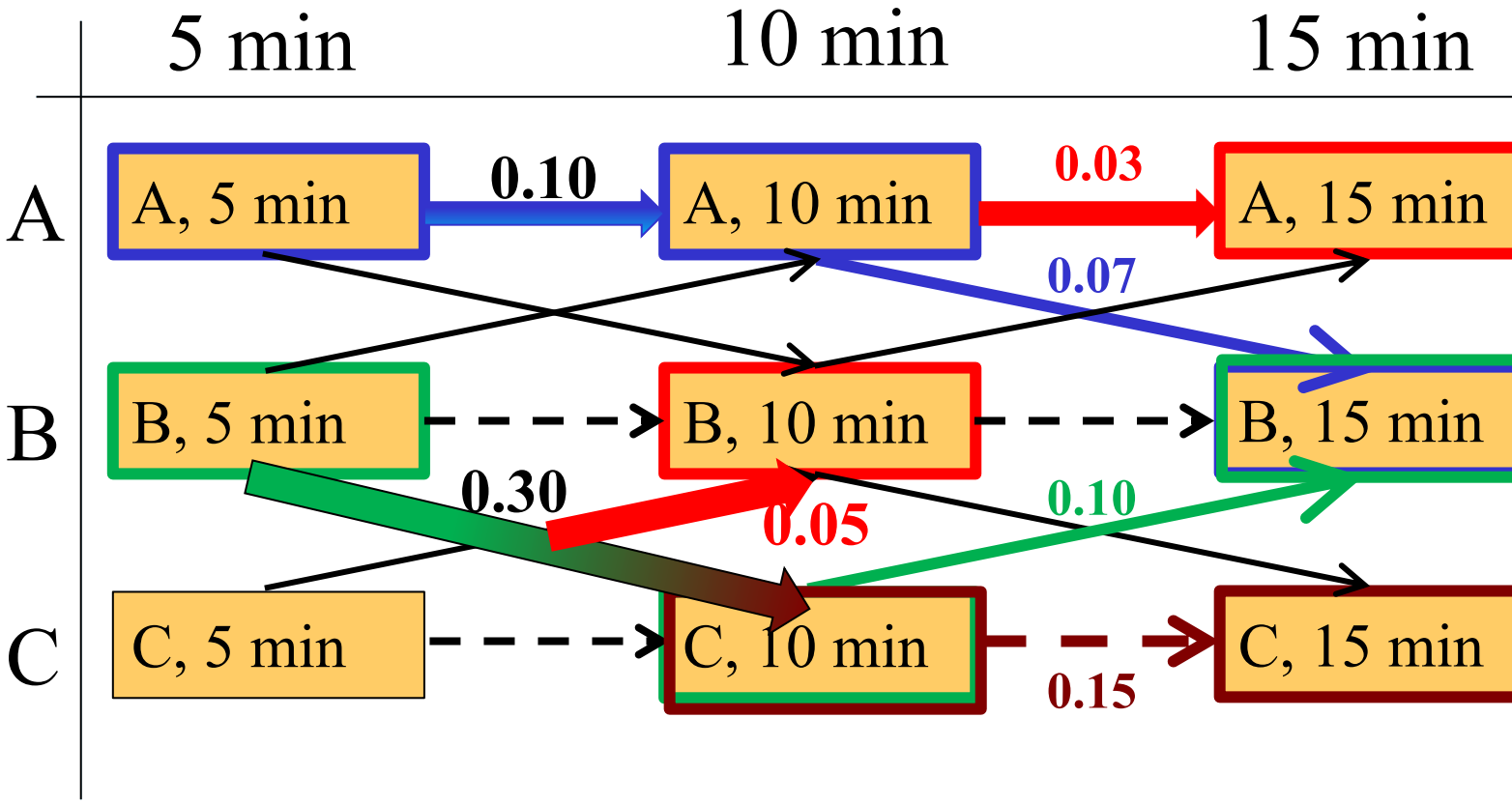

Jiang *Delle Fave*



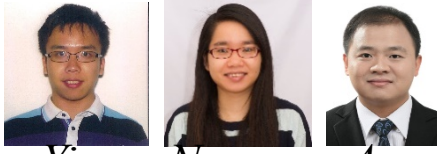
TRUSTS: Patrols Against Fare Evaders
Uncertainty in Defender Action Execution

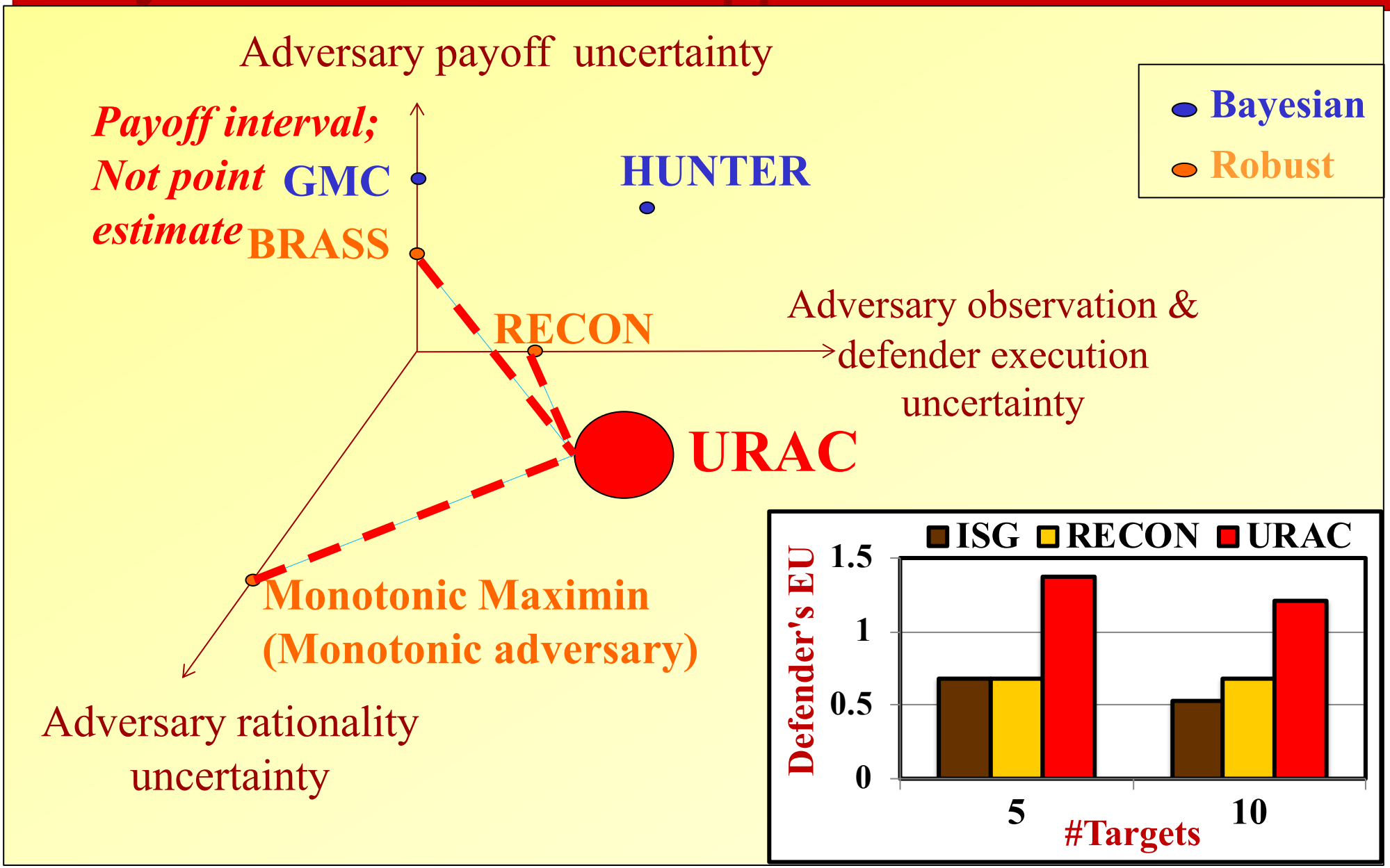

Jiang *Delle Fave*

- Markov Decision Problems *in Security games*

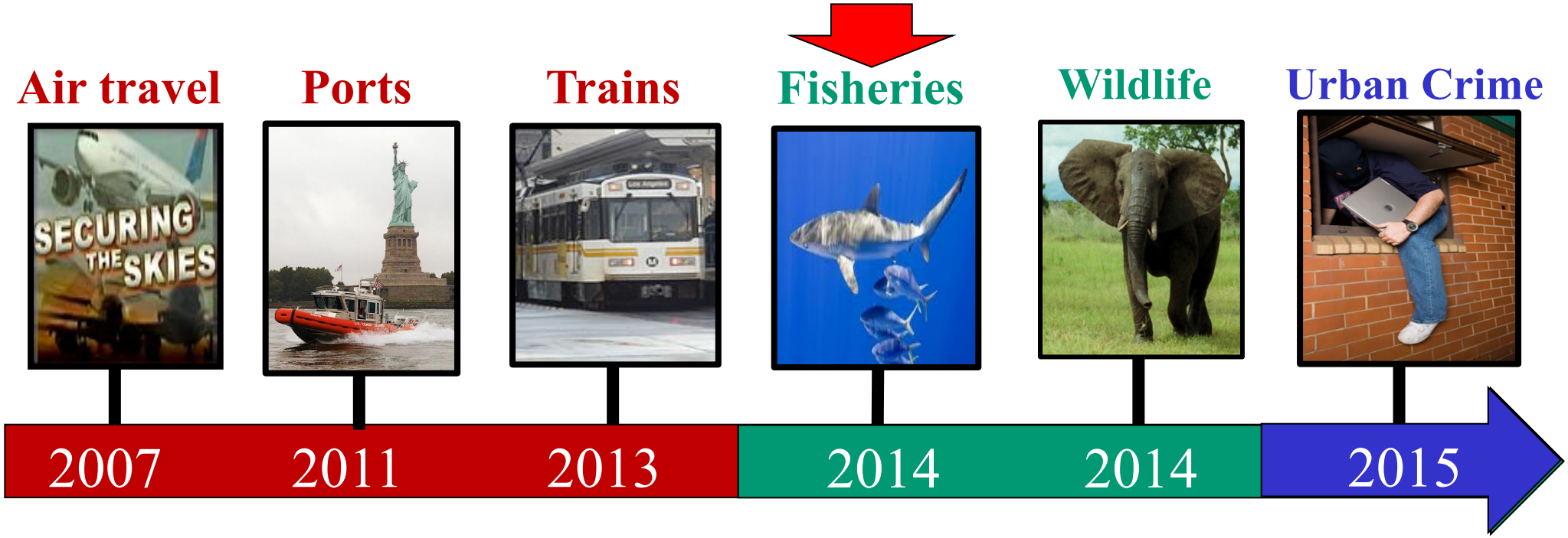


Uncertainty Space Algorithms: Bayesian and Robust Approaches

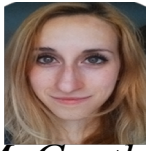


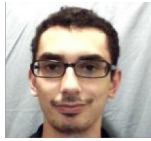


Outline: Security Games Research (2007-)



Protecting Forests, Fish, Rivers & Wildlife: Green Security Games

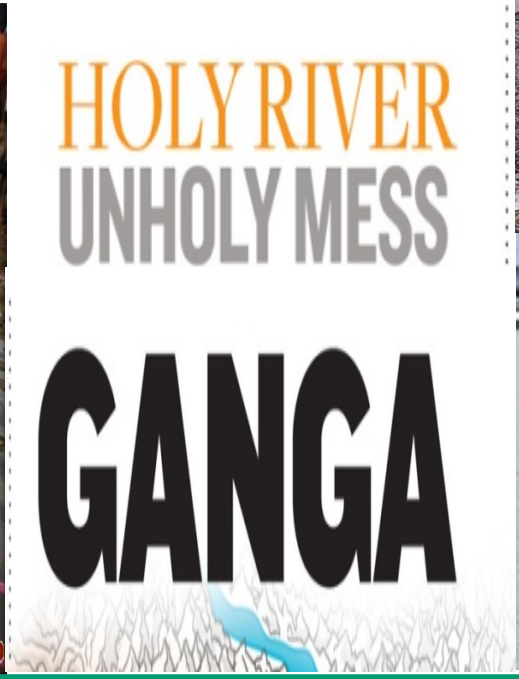




McCarthy Ford Brown

River Pollution Prevention



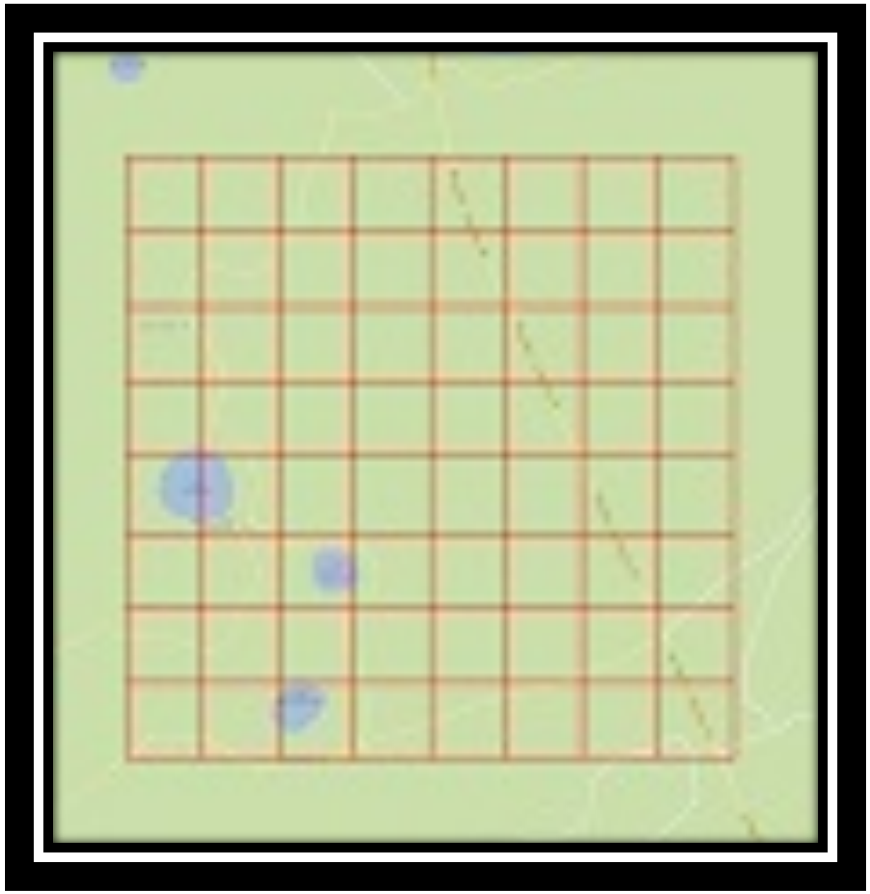



Fishery Protection

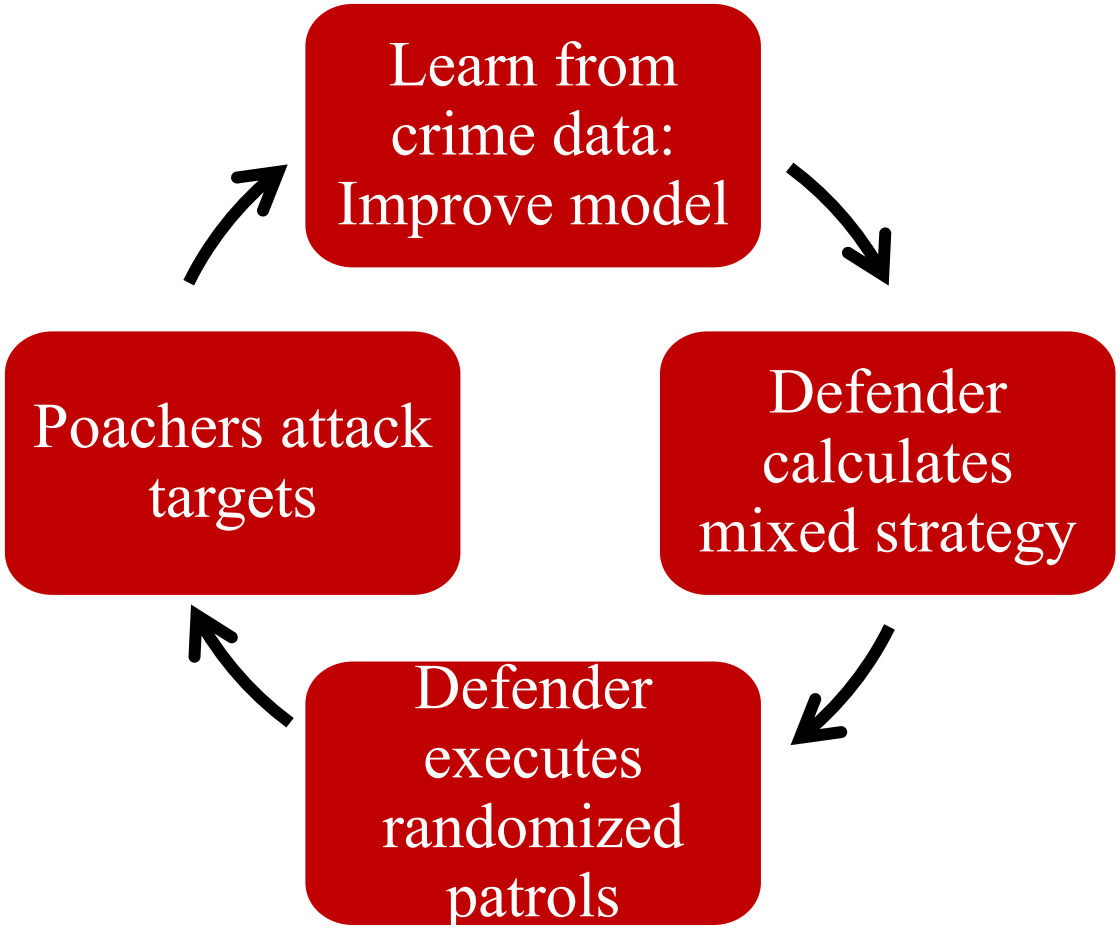
Forest Protection

Wildlife Protection:
Murchison Falls National Park, Uganda

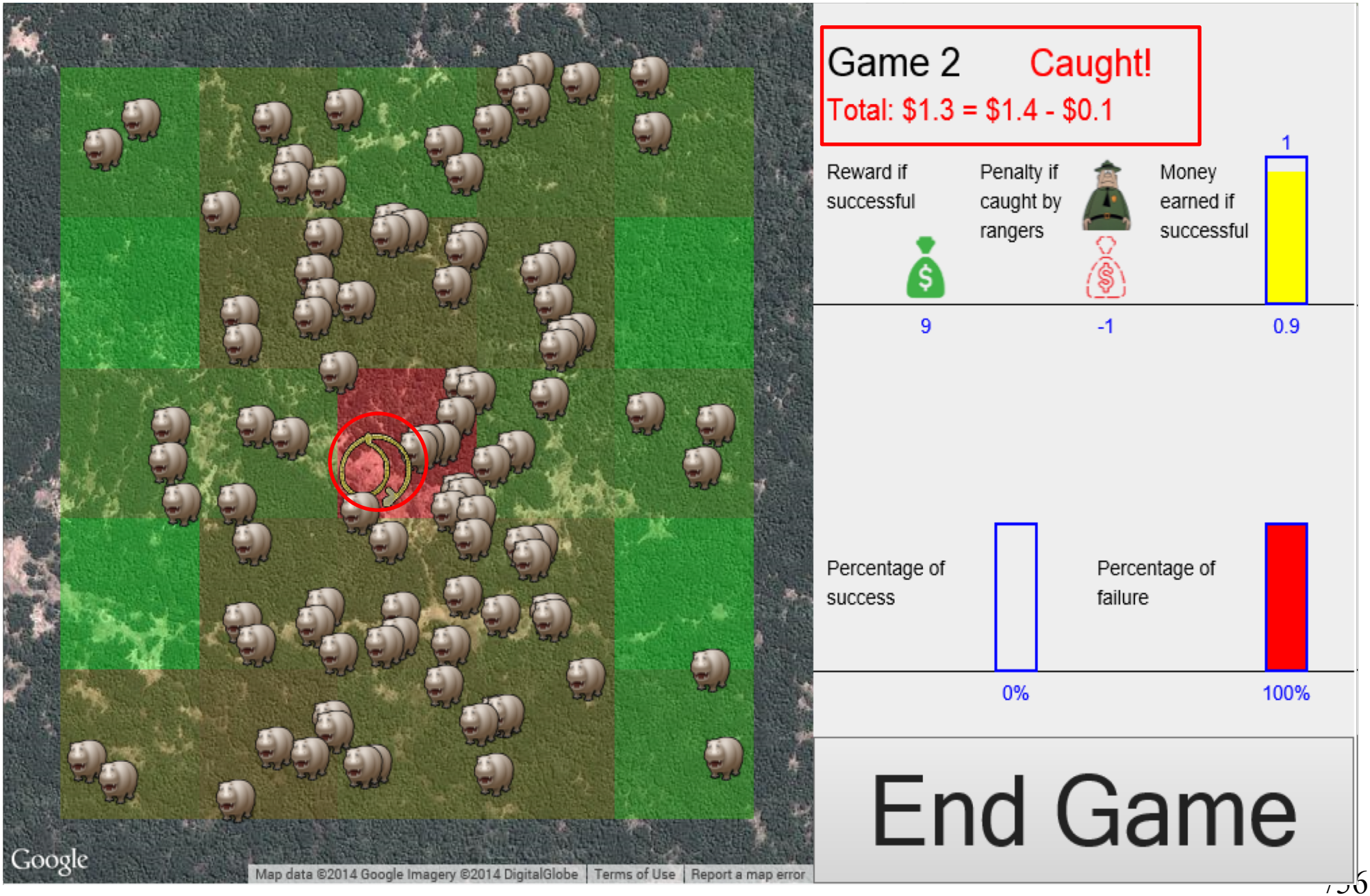
Green Security Games: Repeated Stackelberg Game



Bounded rationality model of poachers



Uncertainty in Adversary Decision: Bounded Rationality
Human Subjects as Poachers



Lesson 1: Quantal Response [2011]: Models of Bounded Rationality

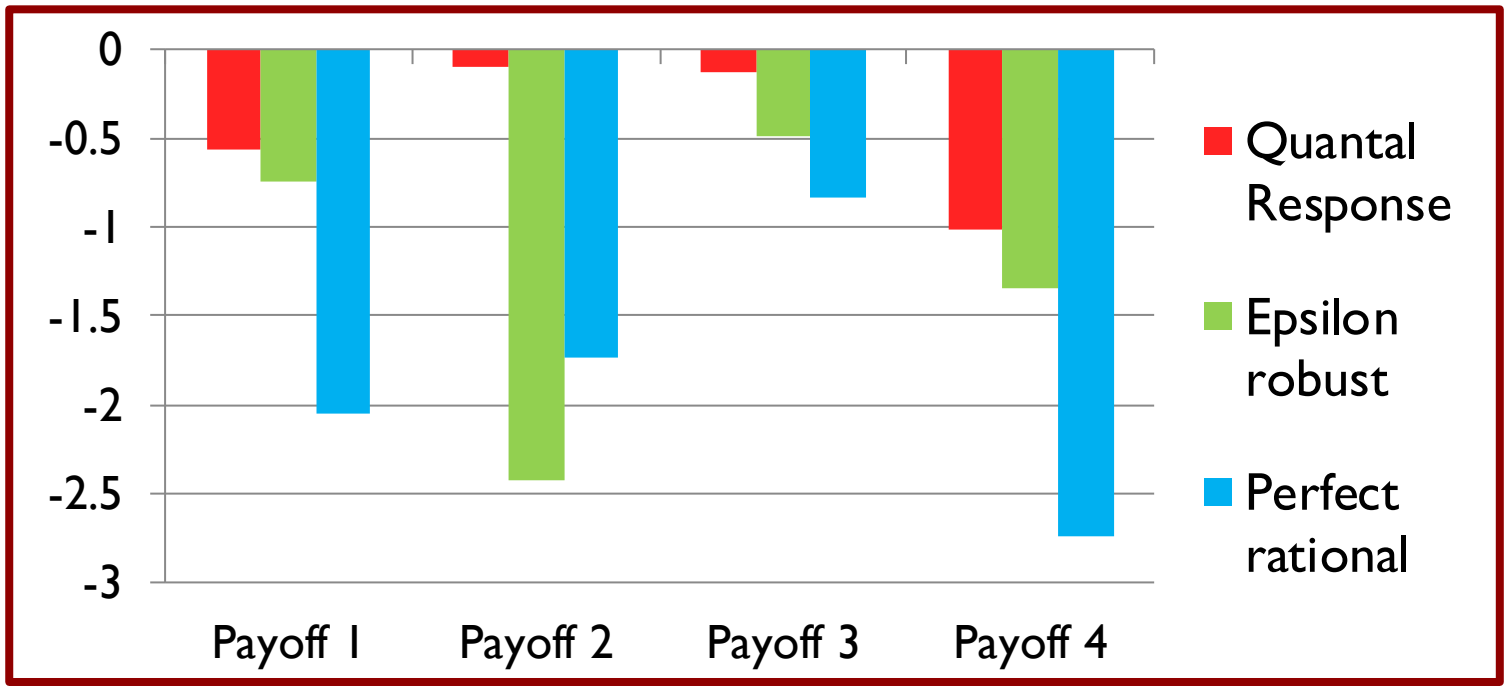

Pita


Yang

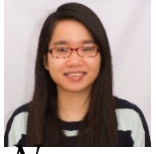
Perfect: $EU^{adversary}(j) = Capture\text{Prob} \times \text{Penalty} + (1 - Capture\,\text{Prob}) \times \text{Reward}$

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

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



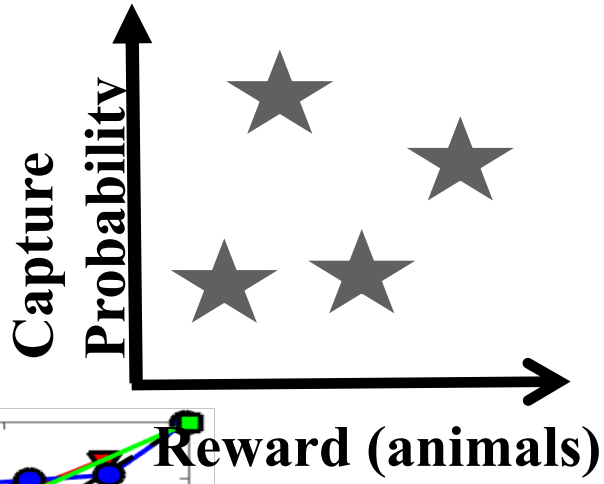
Lesson 2: Subjective Utility Quantal Response Models of Bounded Rationality



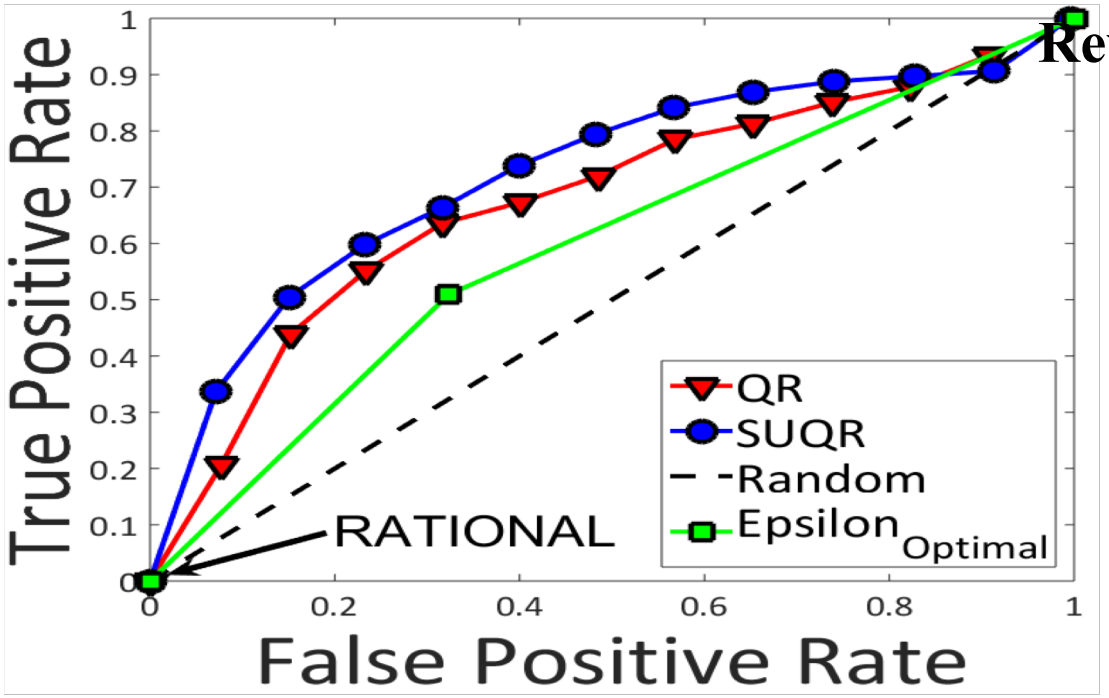
Subjective Utility Quantal Response(SUQR) [Nguyen 13]:

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

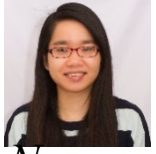
Adversary's probability of **choosing target j** $= \dfrac{e^{SEU^{adversary}(x,j)}}{\sum_{j'=1}^{M} e^{SEU^{adversary}(x,j')}}$

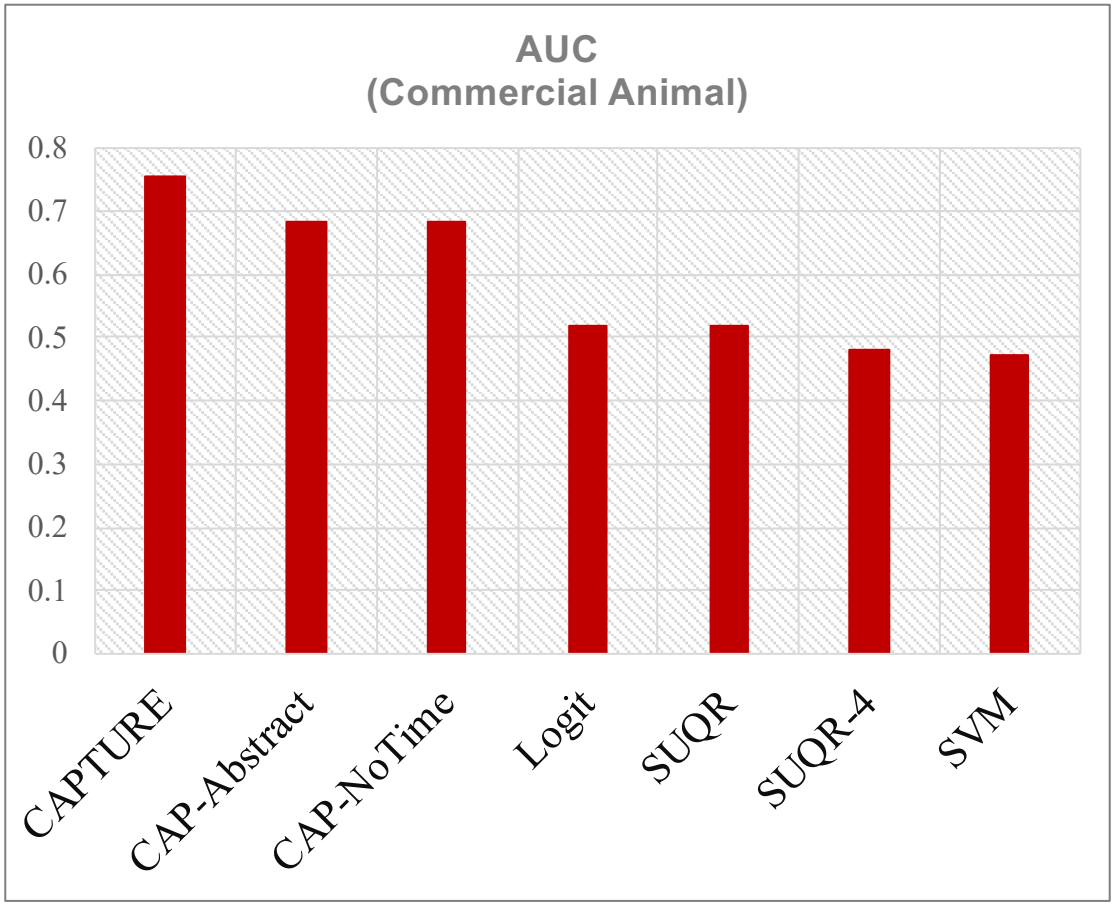


UWA data from Uganda: Year 2012 Predicting poaching

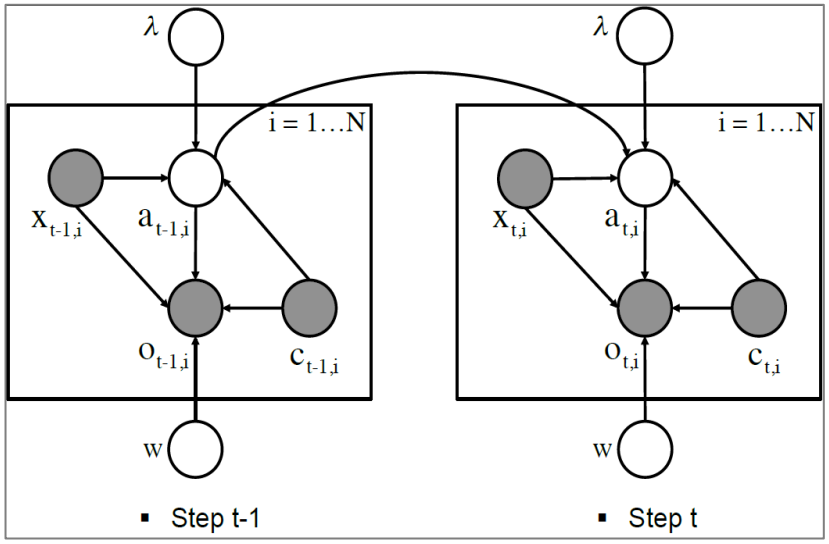


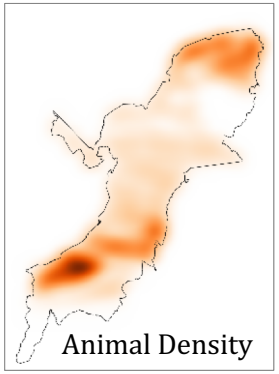
CAPTURE
Predictive Anti-Poaching Tool for Wildlife Protection

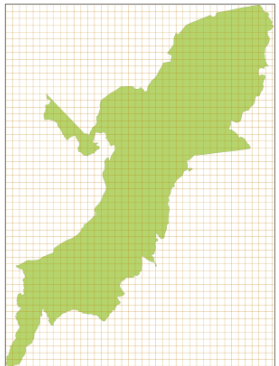




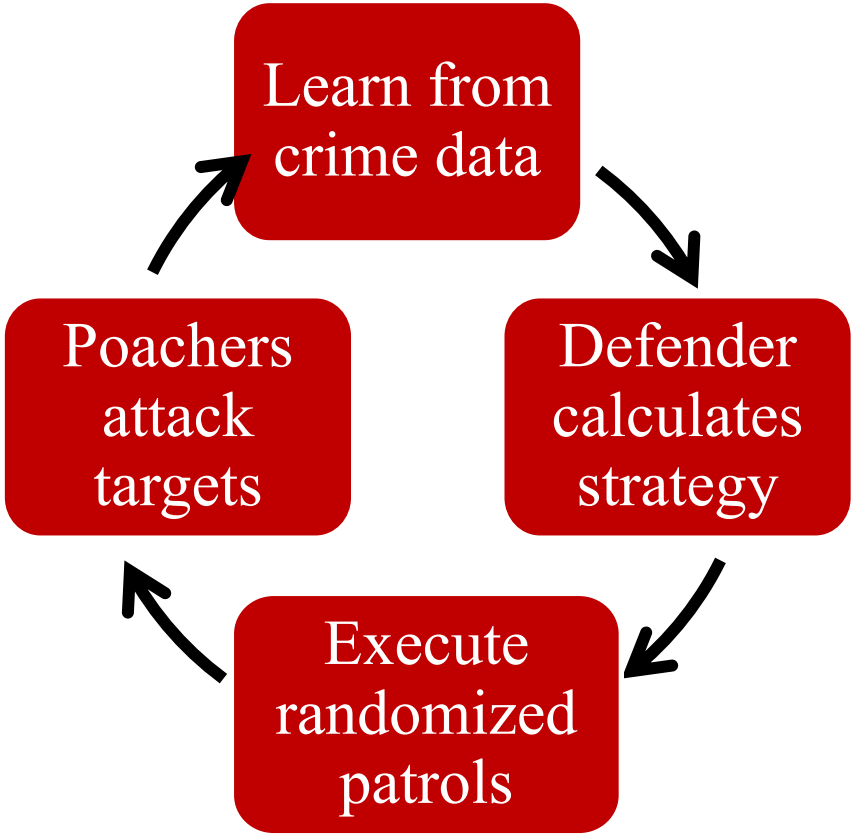
12 years of Uganda data



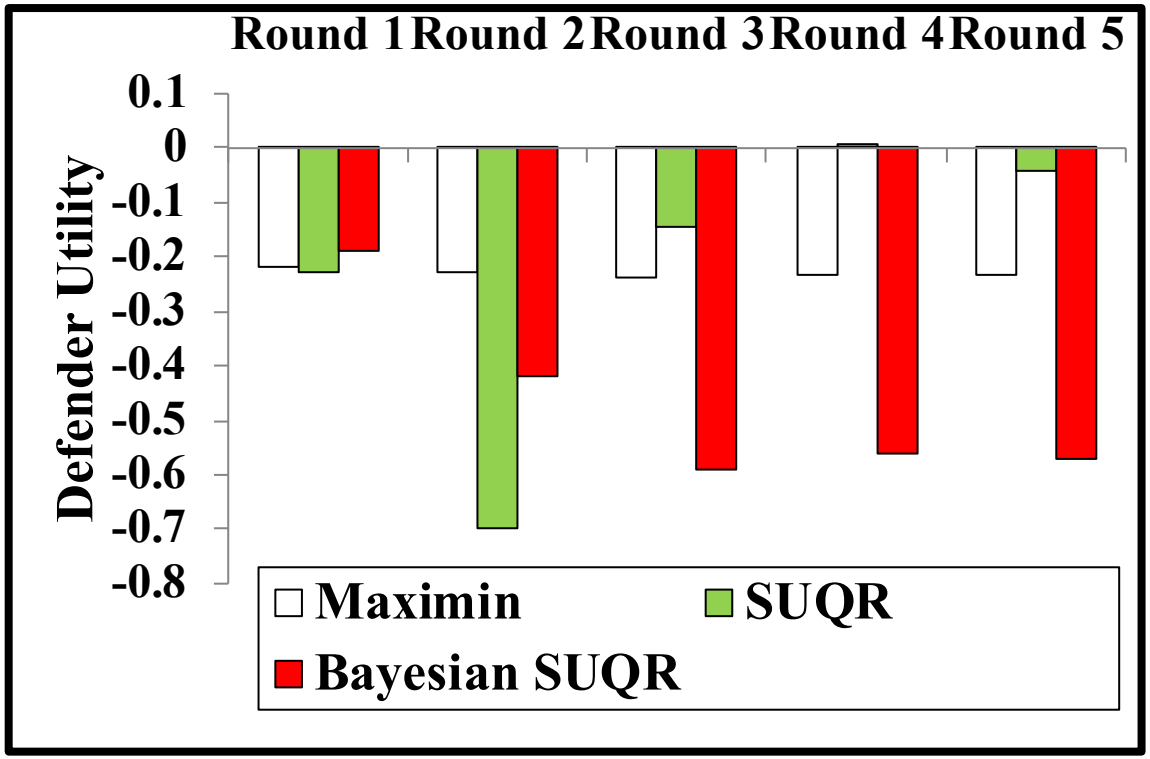




Green Security Games[2015]
Testing SUQR: From One-Shot to Repeated Games

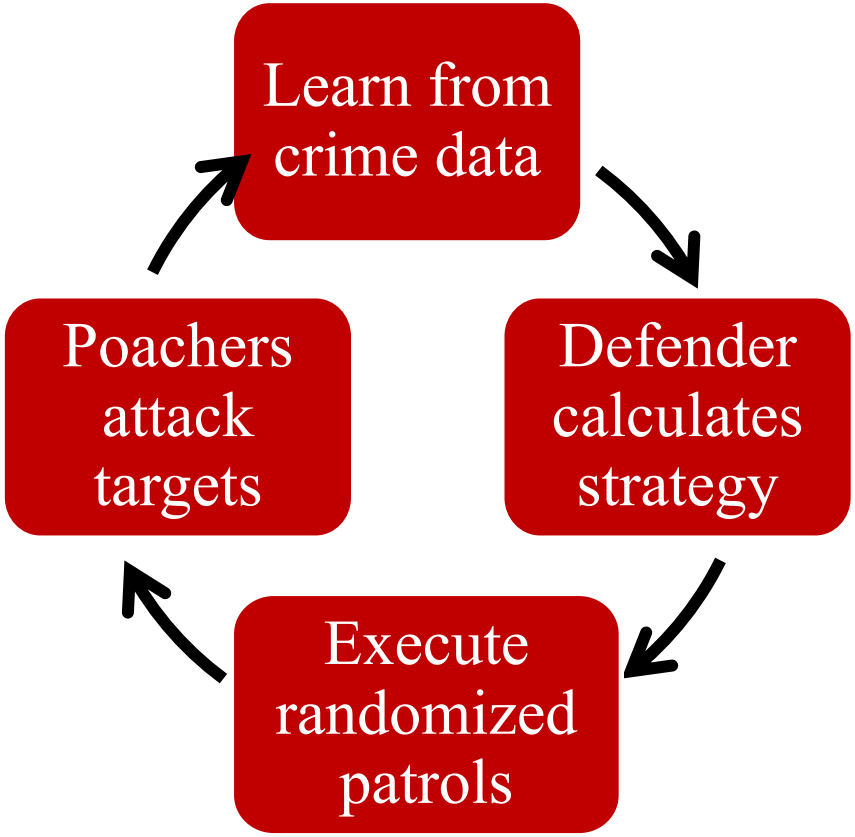


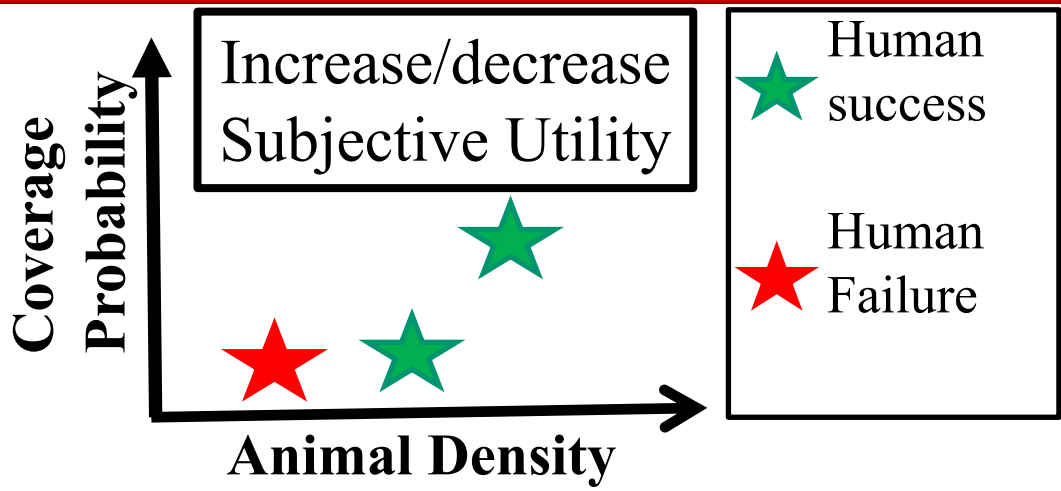
Repeated games on AMT:
35 weeks, 40 human subjects
10,000 emails!

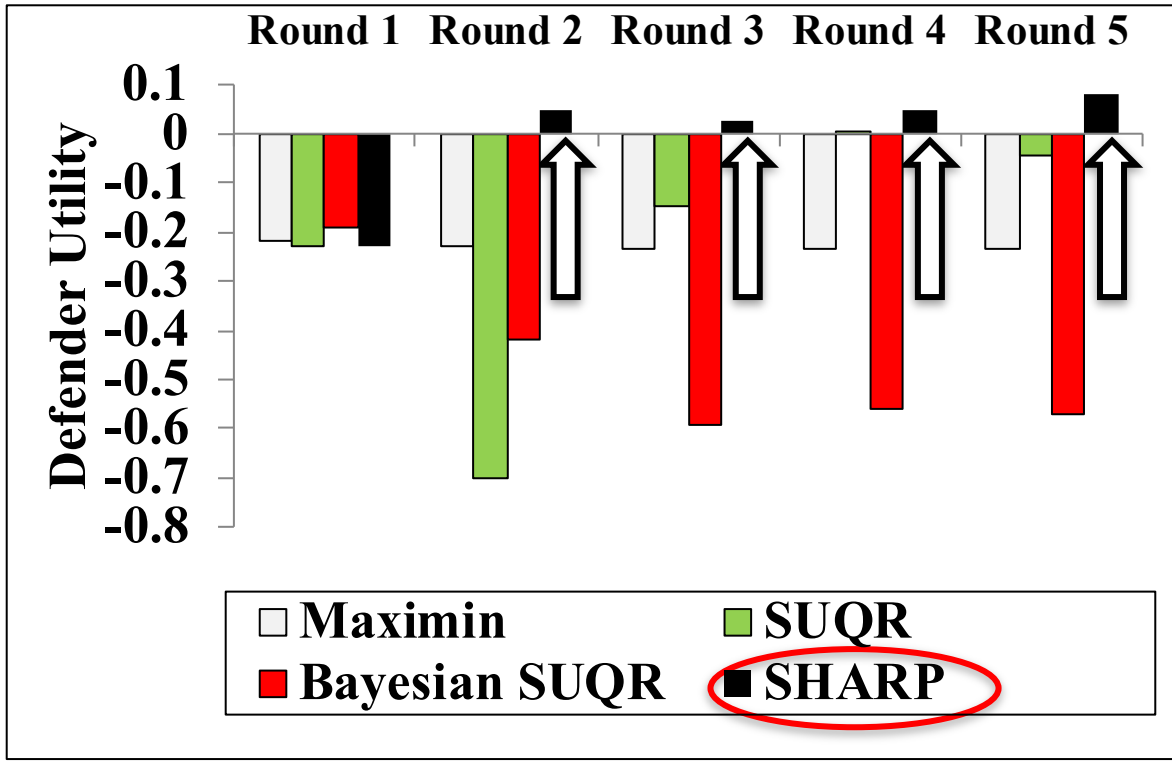


Lesson 3: SHARP and Repeated Stackelberg Games Incorporate Past Success/Failure in SUQR

Kar

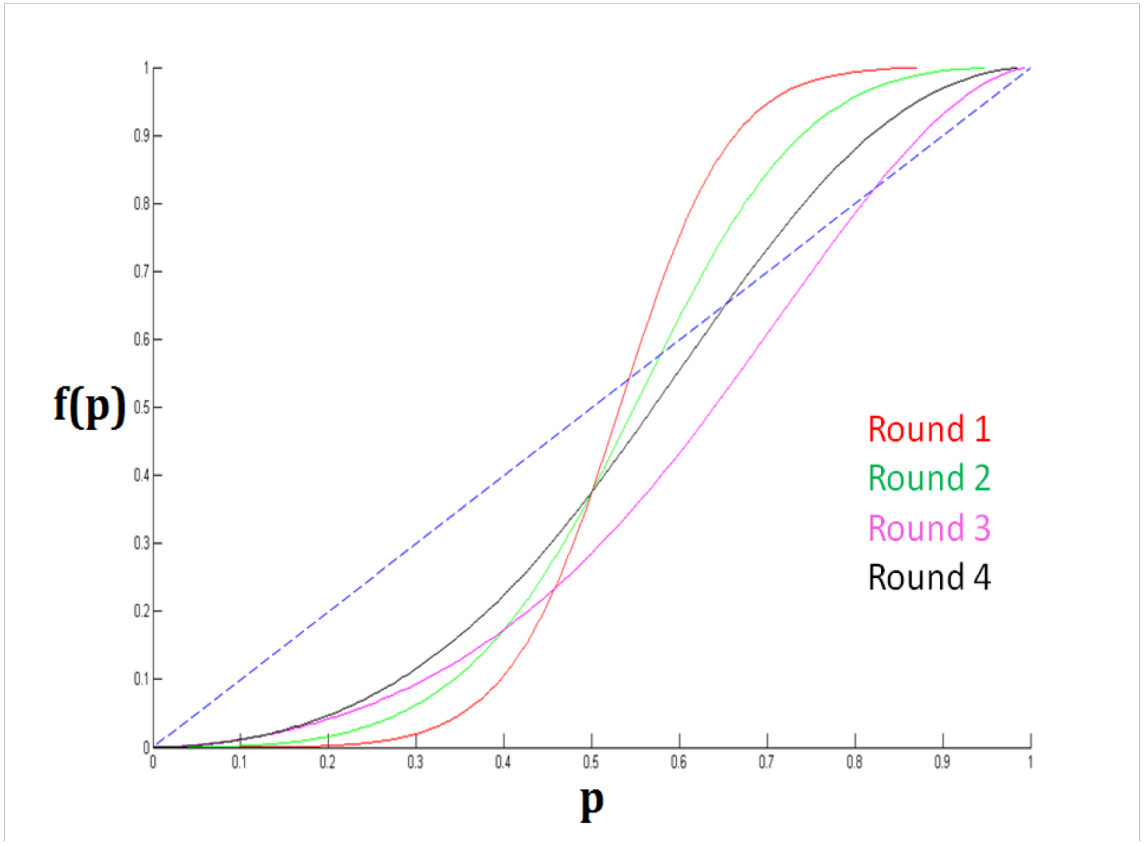






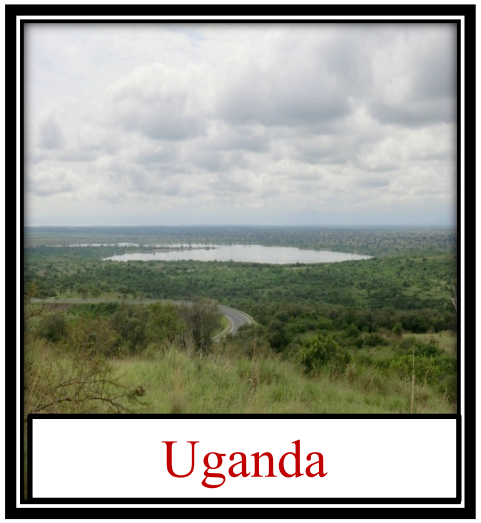
Learned Probability Weighting Function

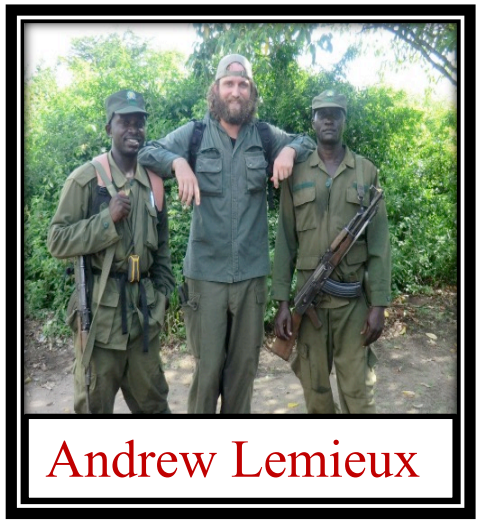
- Adversary's probability weighting function is S-shaped.
  - *Contrary to Prospect Theory (Kahneman '79).*



PAWS: Protection Assistant for Wildlife Security Trials in Uganda and Malaysia: [2014]

- **Important lesson: Geography!**

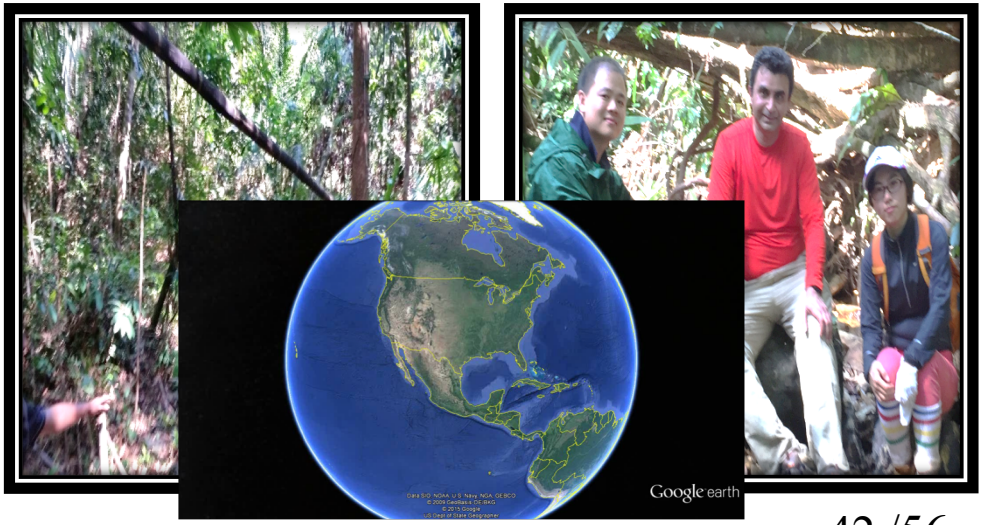

Uganda


Andrew Lemieux


Malaysia


Panthera

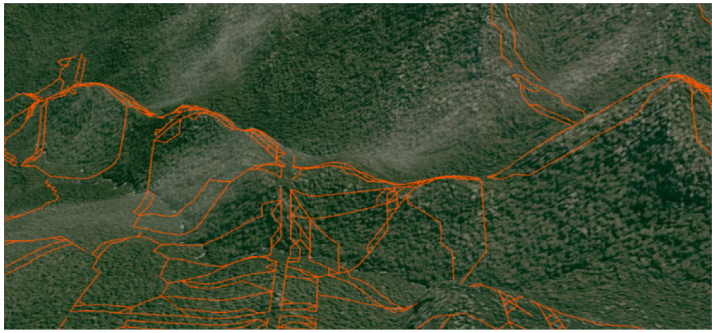

Malaysia



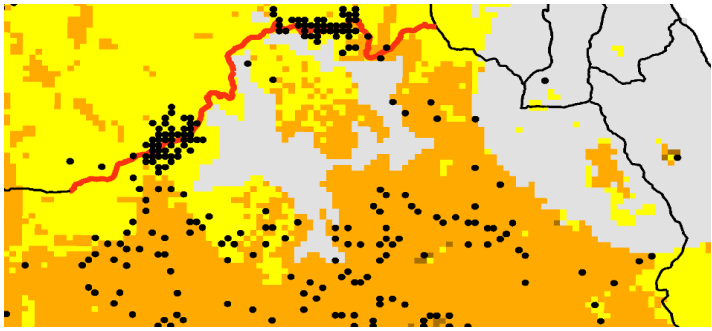
PAWS for Wildlife Security: Scale, Uncertainty in Green Security Games


Fang

- Scale: Hierarchical model
  - *Hierarchical: Grid + "Street map"*



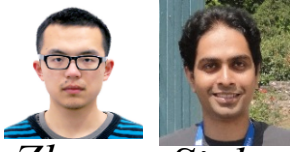
- Species location uncertainty



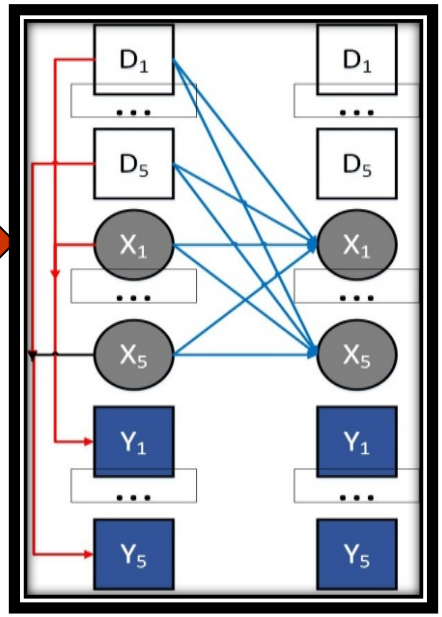
- ***In regular use in Malaysia***



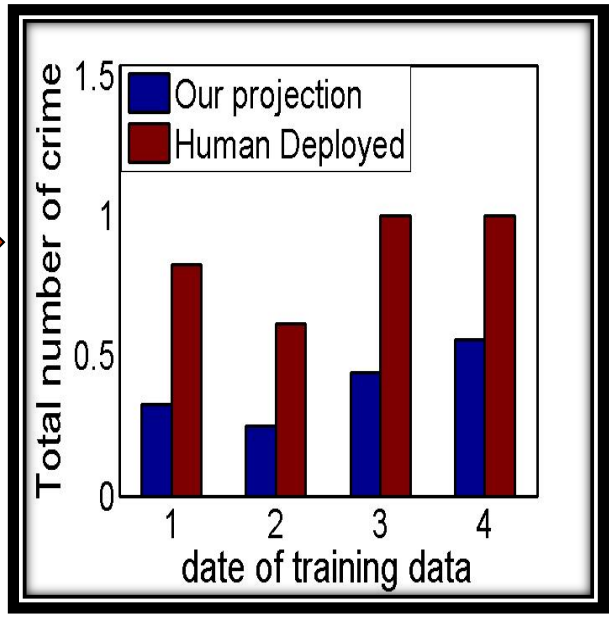
Opportunistic Crime Security Game[2015]
Integrating Learning in Basic Security Game Model

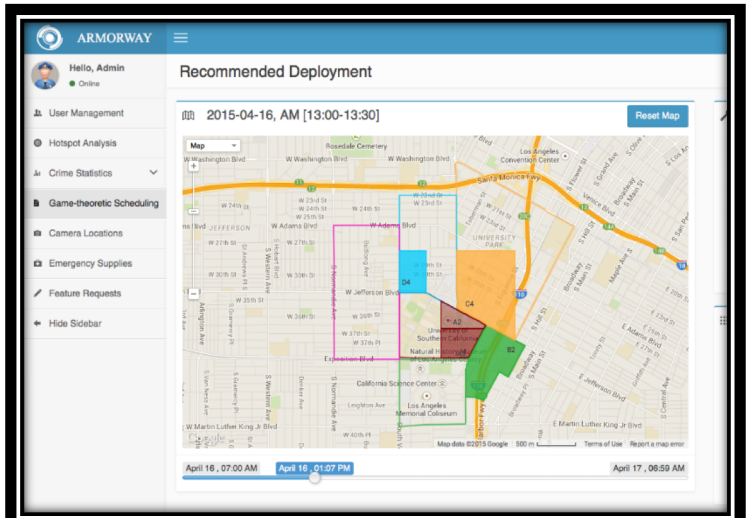


- Crime prediction: use past crime & police allocation data



Best Simulation Results





Evaluating *Deployed Security Systems* Not Easy: Are Security Games Better at Optimizing Limited Resources

- Security games improve over humans (or simple) planners
  - *E.g., humans fall into predictable patterns; high cognitive load*

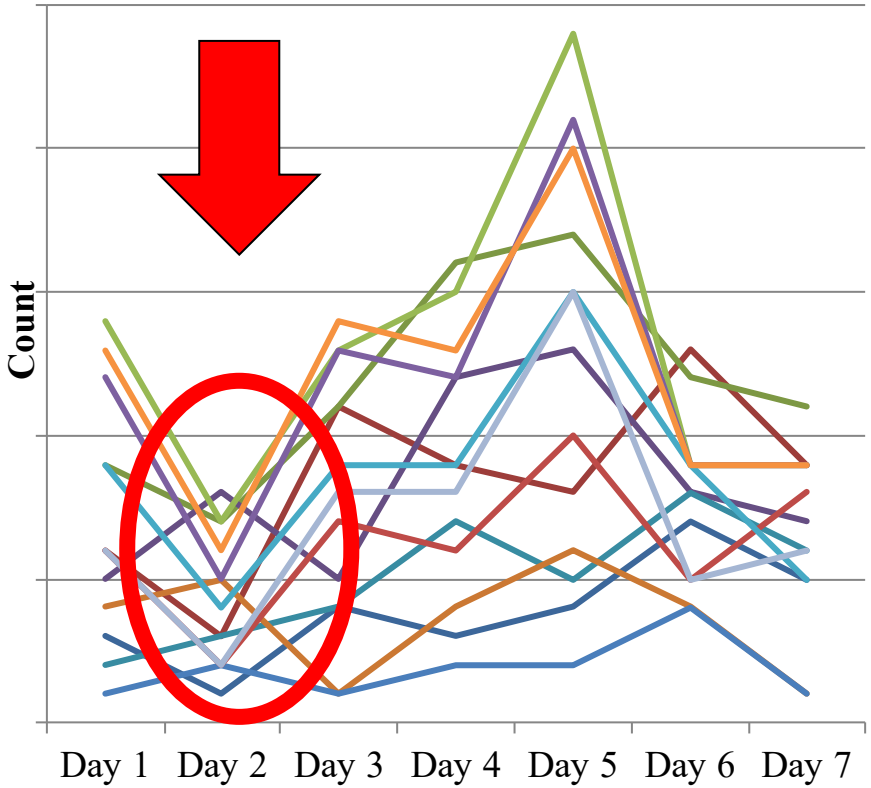
Lab Evaluation	Field Evaluation: Patrol quality Unpredictable? Cover?	Field Evaluation: Tests against adversaries
Simulated adversary	Compare real schedules	"Mock attackers"
Human subject adversaries	Scheduling competition	Capture rates of real adversaries
	Expert evaluation	

Field Evaluation of Schedule Quality:

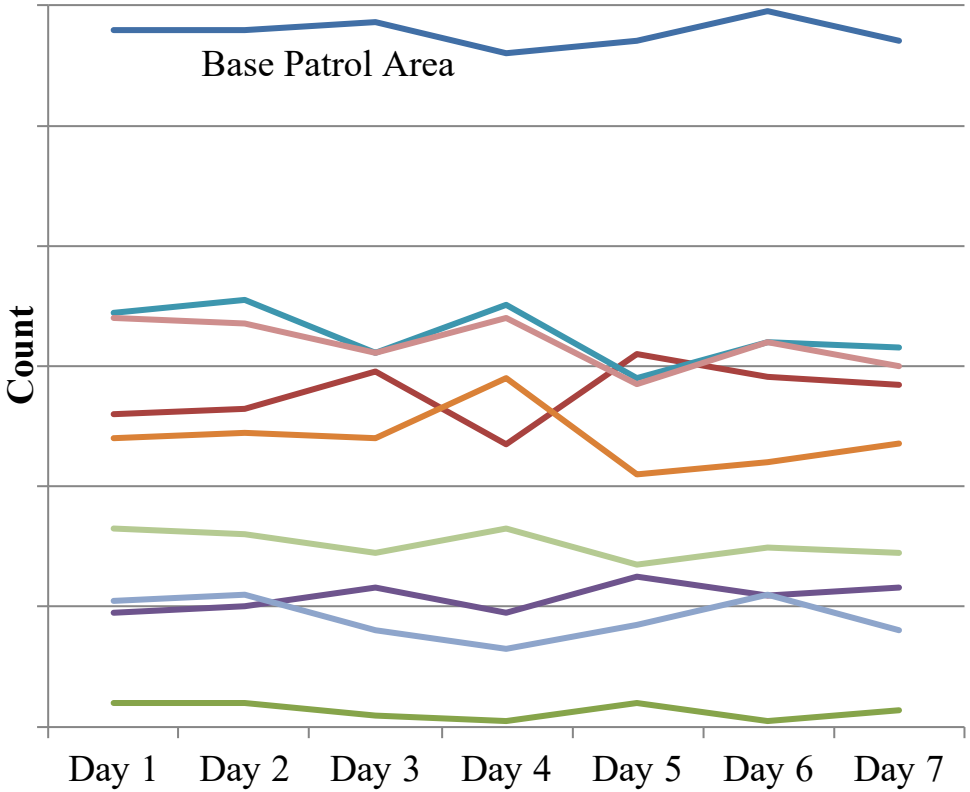
Improved Patrol Unpredictability & Coverage for Less Effort

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

Patrols Before PROTECT: Boston



Patrols After PROTECT: Boston



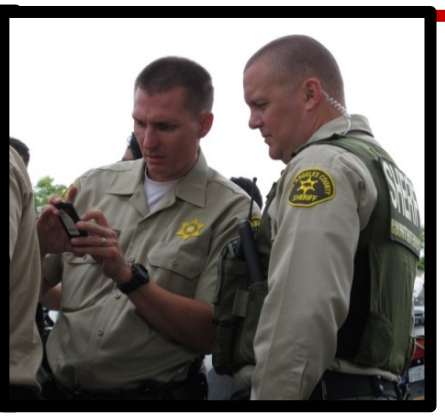
Field Evaluation of Schedule Quality:

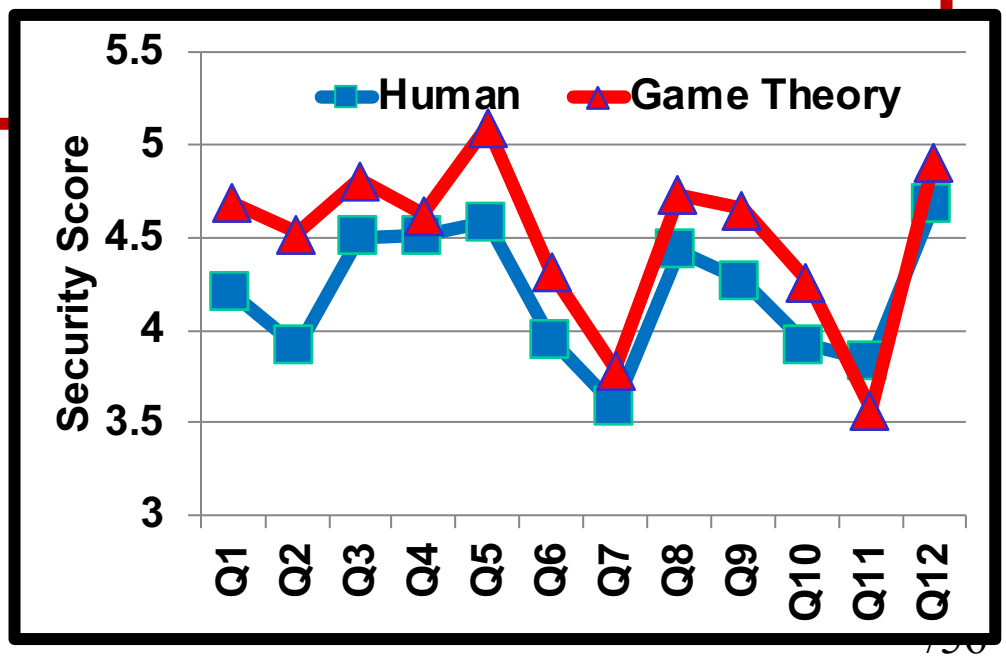
Improved Patrol Unpredictability & Coverage for Less Effort

FAMS: IRIS Outperformed expert human over six months

Report:GAO-09-903T

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





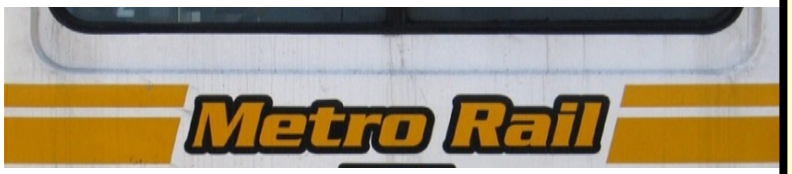
Field Test Against Adversaries: Mock Attackers Example from PROTECT

- "Mock attacker" team deployed in Boston
  - *Comparing PRE- to POST-PROTECT: "deterrence" improved*

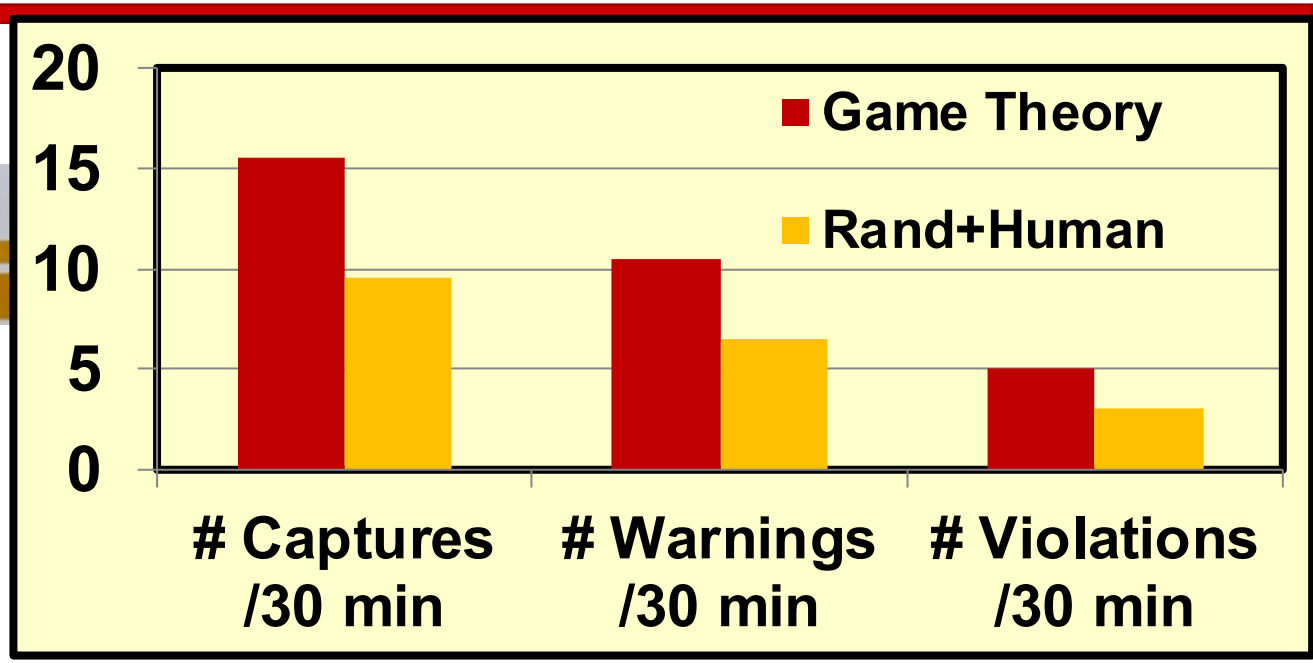
- Additional real-world indicators from Boston:
  - *Boston boaters questions:*
    - "..has the Coast Guard recently acquired more boats"

Field Tests Against Adversaries
Computational Game Theory in the Field

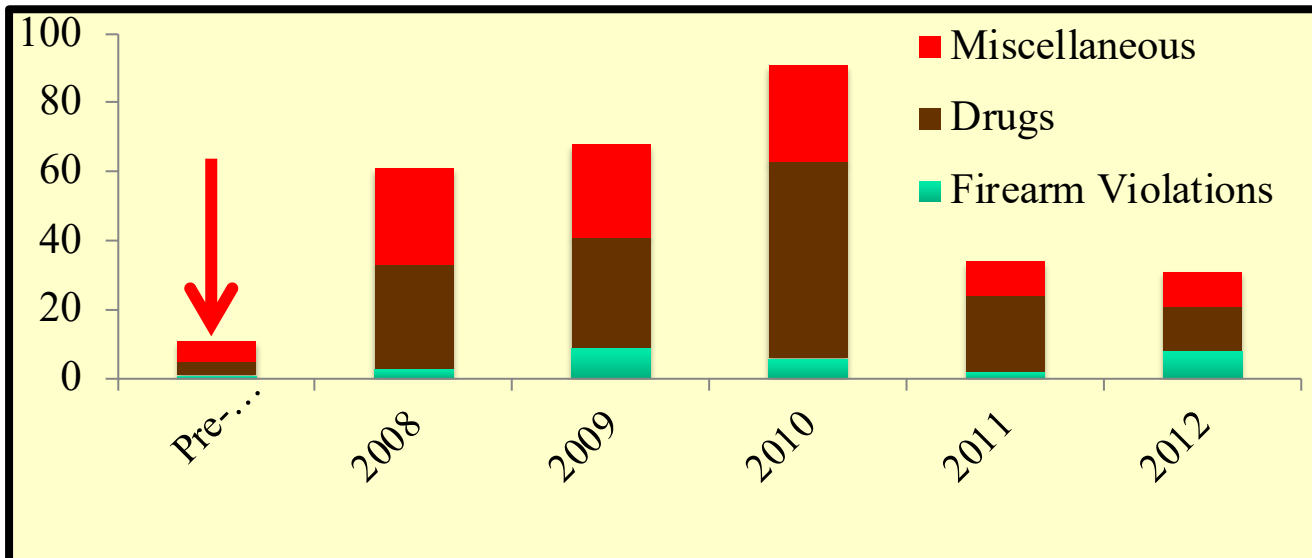
Controlled



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

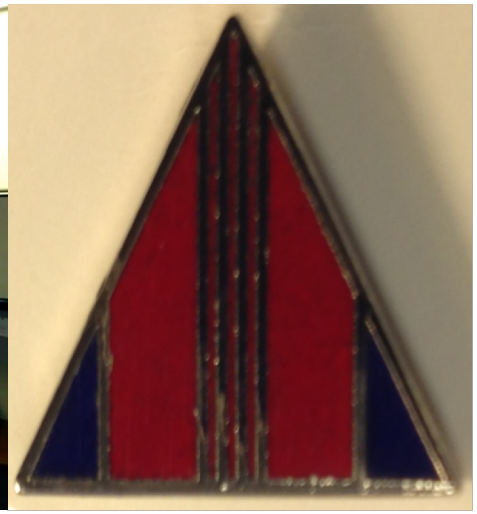


Not controlled



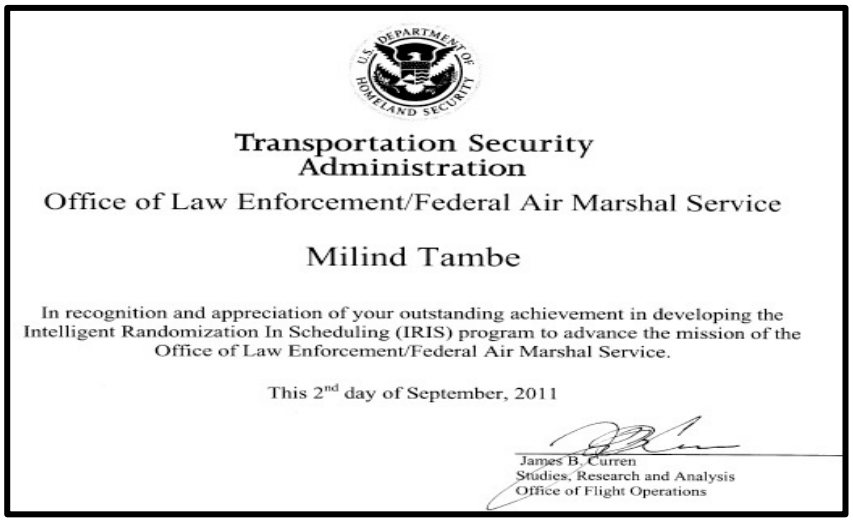
User Feedback
Example from ARMOR, IRIS & PROTECT

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



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

September 2011: Certificate of Appreciation (Federal Air Marshals)



U.S. DEPARTMENT OF HOMELAND SECURITY

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

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

Global Efforts on Security Games: Yet Just the Beginning…

Thank you to sponsors:

CREATE HOMELAND SECURITY CENTER

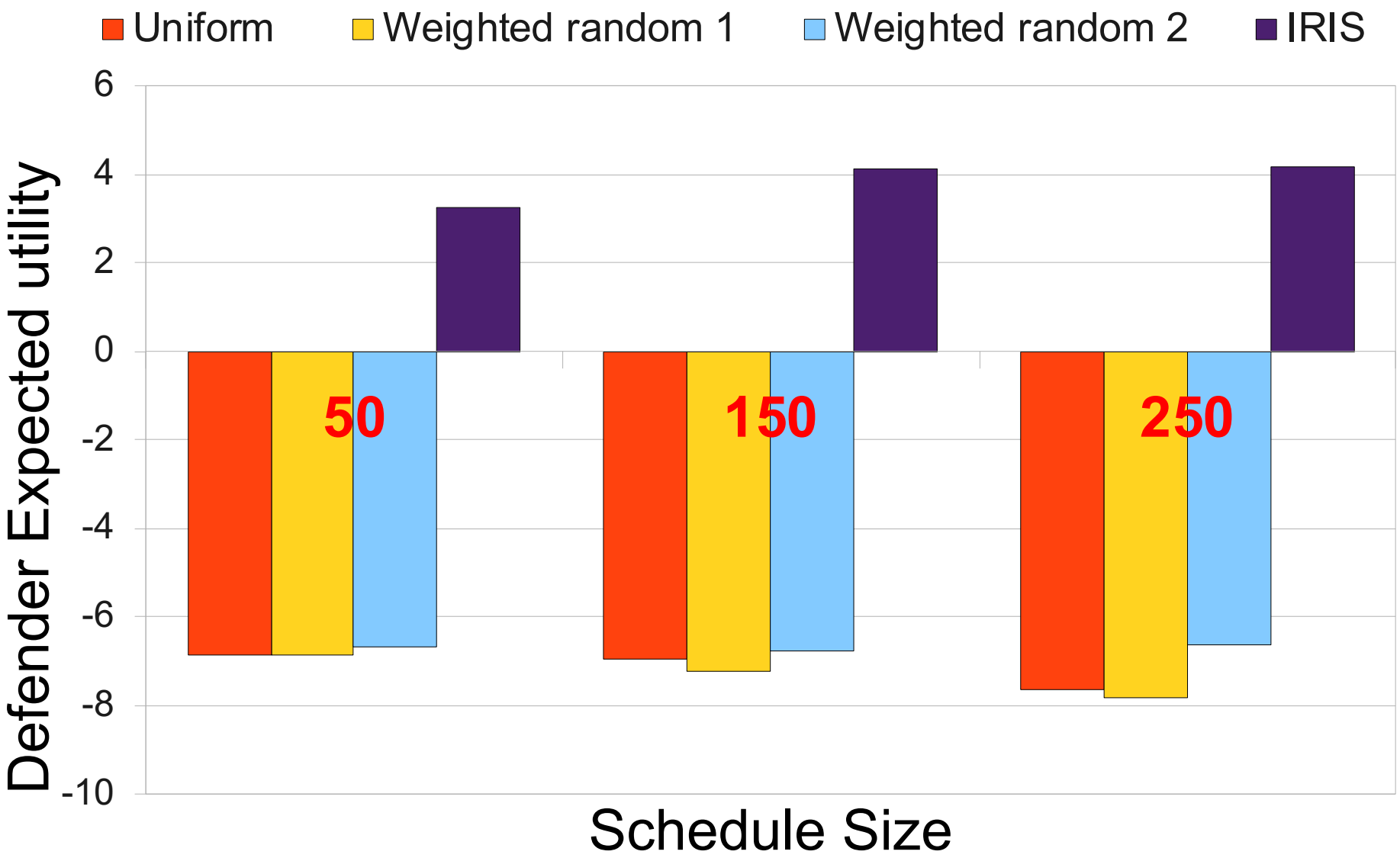
Transportation Security Administration

Army Research Office

THANK YOU

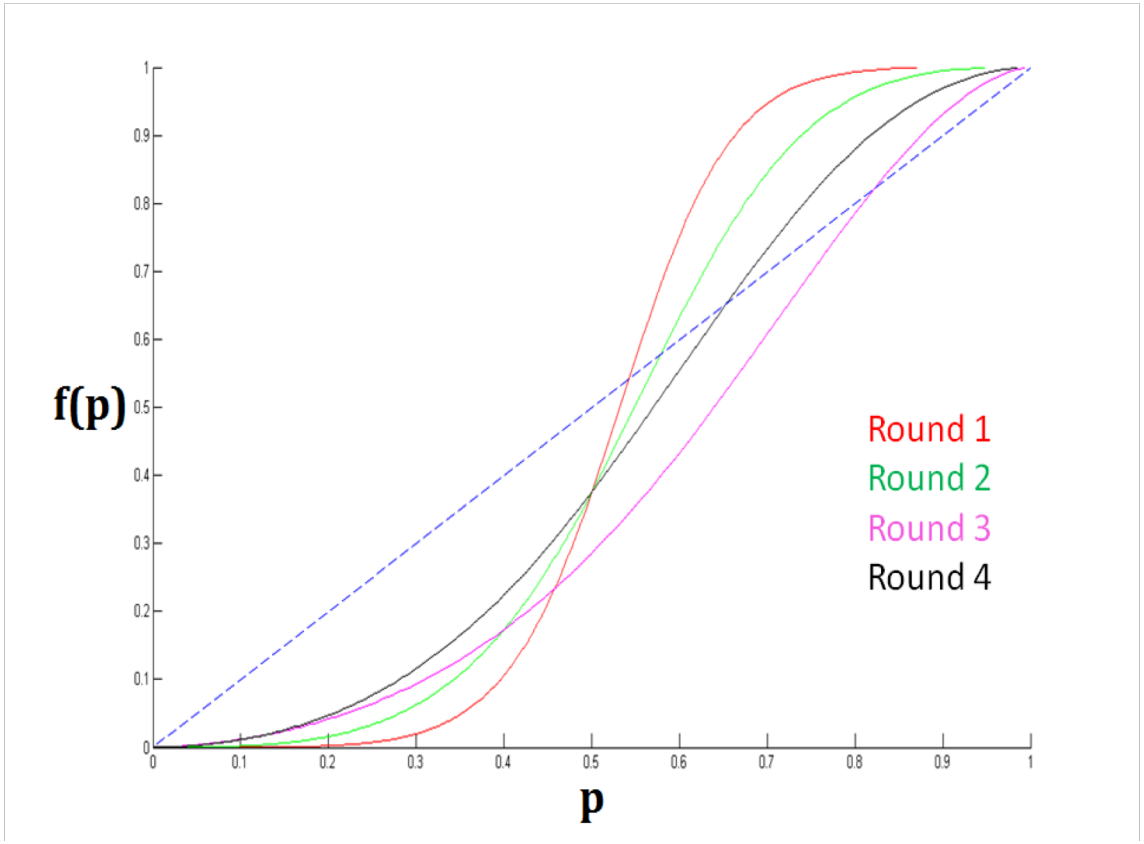
tambe@usc.edu
http://teamcore.usc.edu/security

Lab Evaluation via Simulations: Example from IRIS (FAMS)



Learned Probability Weighting Function

- Adversary's probability weighting function is S-shaped.
  - *Contrary to Prospect Theory (Kahneman '79).*



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- Additional real-world indicators from Boston:
  - *Boston boaters questions:*
    - "..has the Coast Guard recently acquired more boats"
  - *POST-PROTECT: Actual reports of illegal activity*

NOT VETTED BY CNN

3 of 5

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

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

About this iReport

- Not vetted for CNN

Posted September 8, 2013 by
shortysmom | Follow
Location
Staten Island, New York

I ride the Staten Island Ferry on a daily basis to and from work. We ferry riders have our own personal protectors in the form of the U.S. Coast Guard. The

IRIS: Scale Up [2009]
Small Support Set for Mixed Strategies


Jain Kiekintveld

Small support set size:

- Most xi variables zero

1000 flights, 20 air marshals:

10^{41} *combinations*

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

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

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

~~x123=0.0~~

x124=0.239

~~x135=0.0~~

x378=0.123

	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

Why Does Game Theory Perform Better? Weaknesses of Previous Methods

- Human schedulers:
  - *Predictable patterns, e.g., US Coast Guard*
  - *Scheduling effort & cognitive burden*
- Simple random (e.g., dice roll):
  - *Wrong weights/coverage, e.g. officers to sparsely crowded terminals*
  - *No adversary reactions*
- Multiple deployments over multiple years: without us forcing them

Key Lessons: Security Games

Decision aids based on computational game theory in daily use

- Optimize limited security resources against adversaries

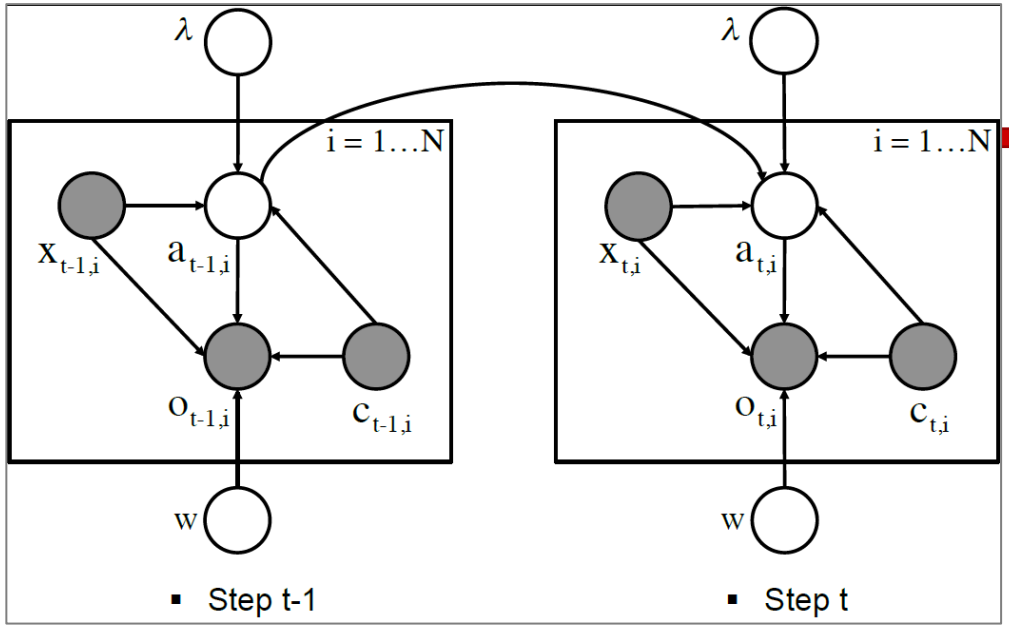
Applications yield research challenges: Science of security games

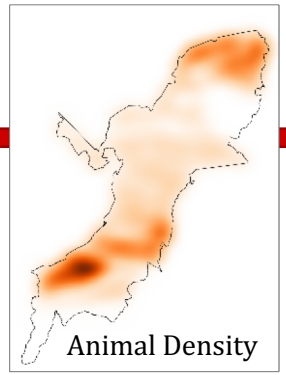
- Scale-up: Incremental strategy generation & Marginals
- Uncertainty: Integrate MDPs, Robustness
- Human behavior: Model innovations based on quantal response

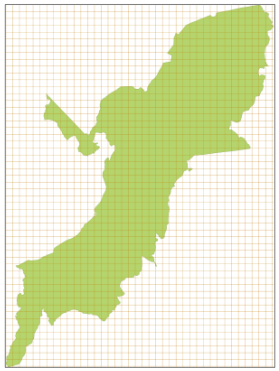
Current applications: Global, interdisciplinary challenges

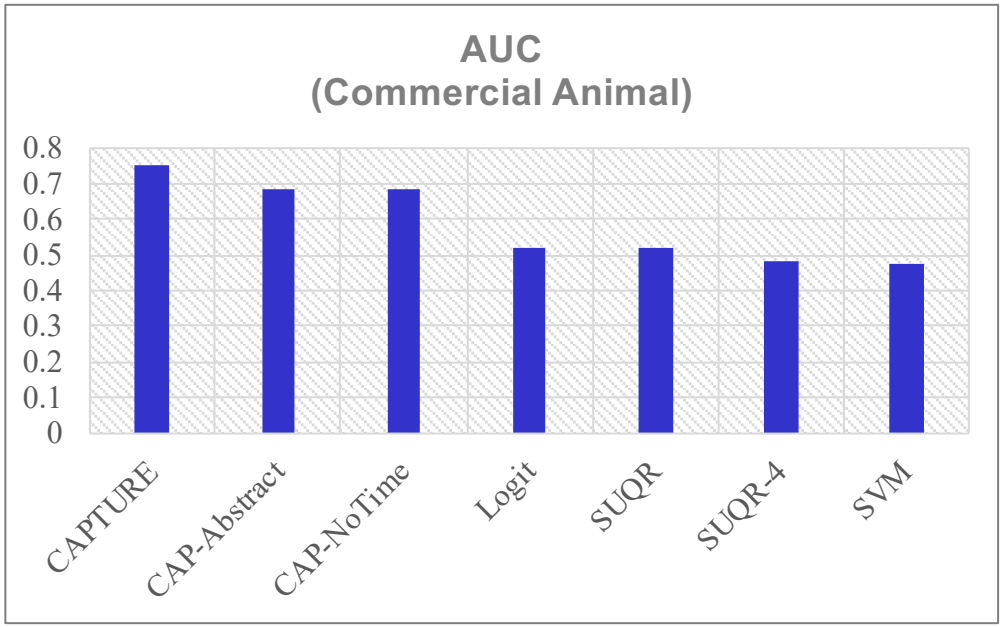
- Green security games: criminology, computation, conservation

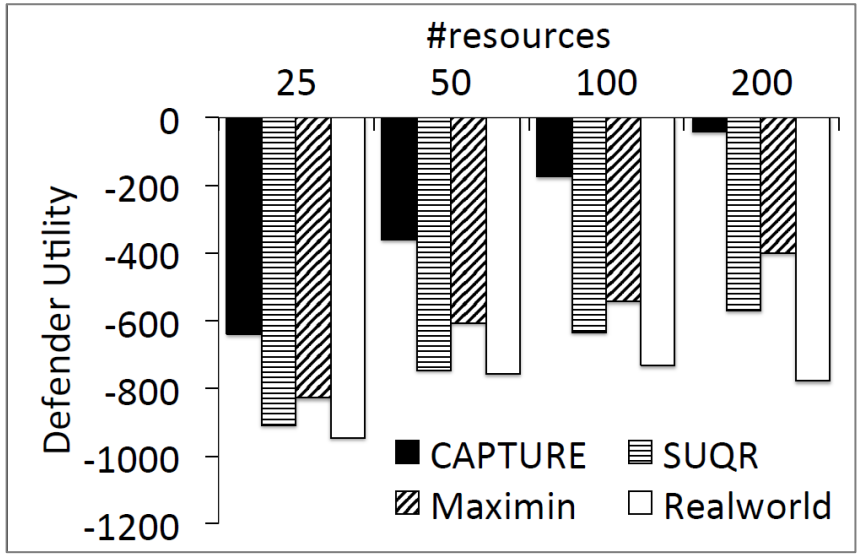
CAPTURE *A New Predictive Anti-Poaching Tool for Wildlife Protection*

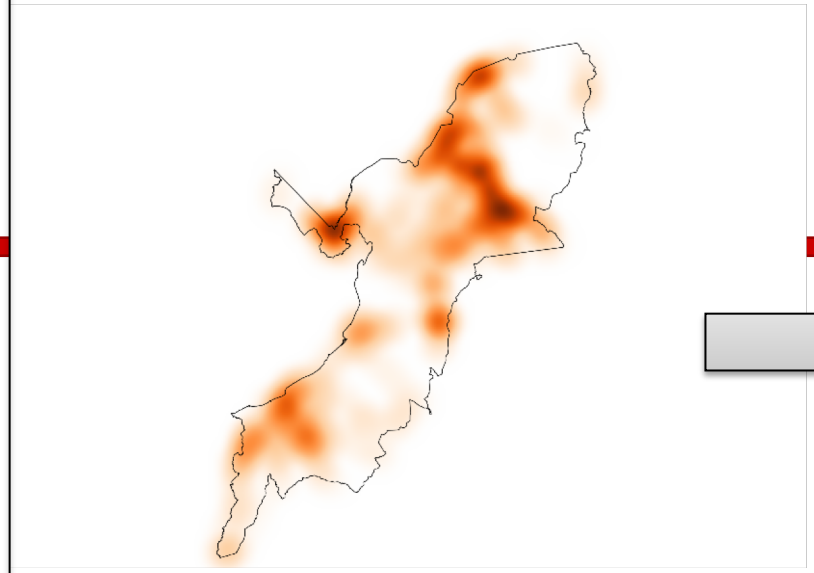




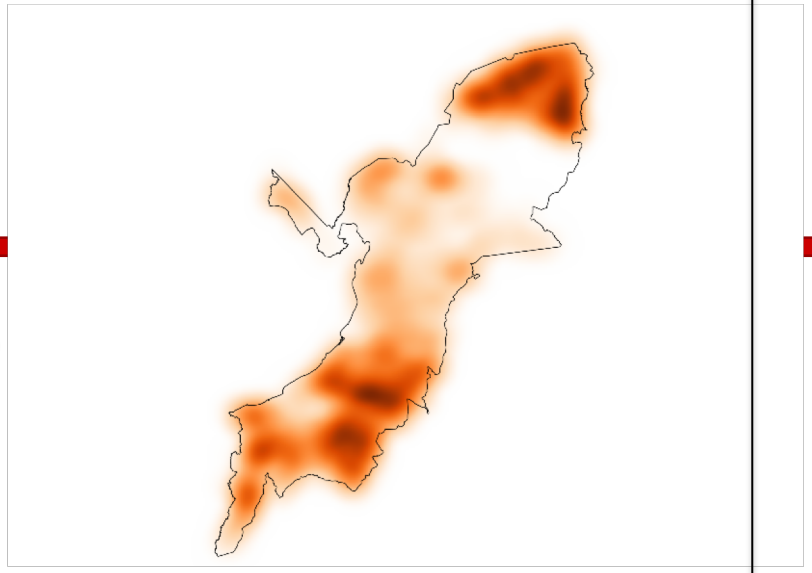




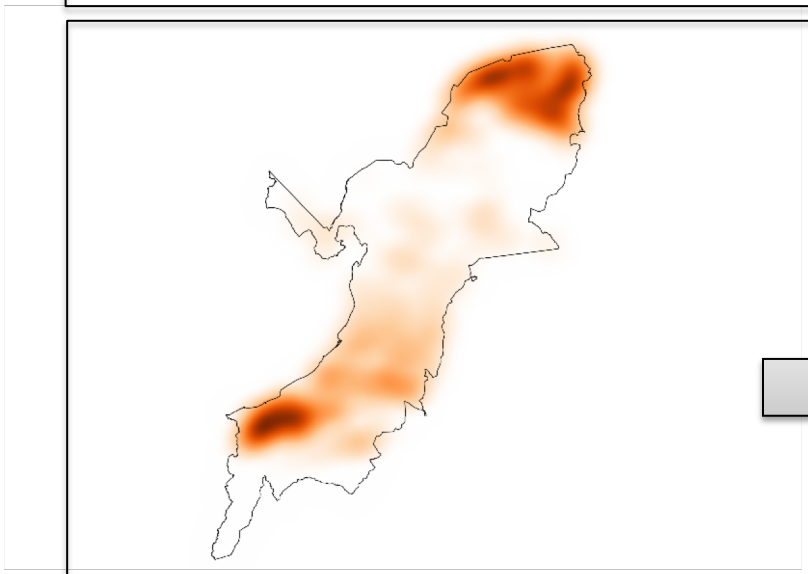




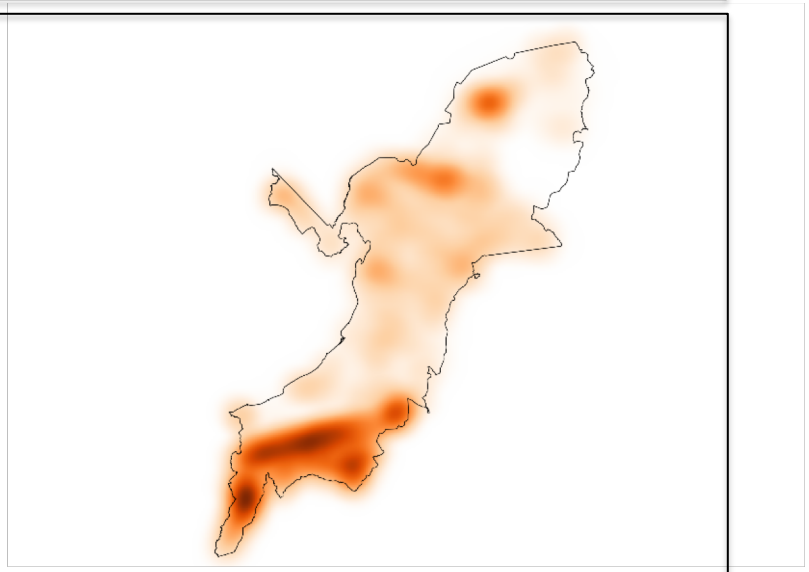
Patrol Strategy (Real)



Attack Probability (CAPTURE)



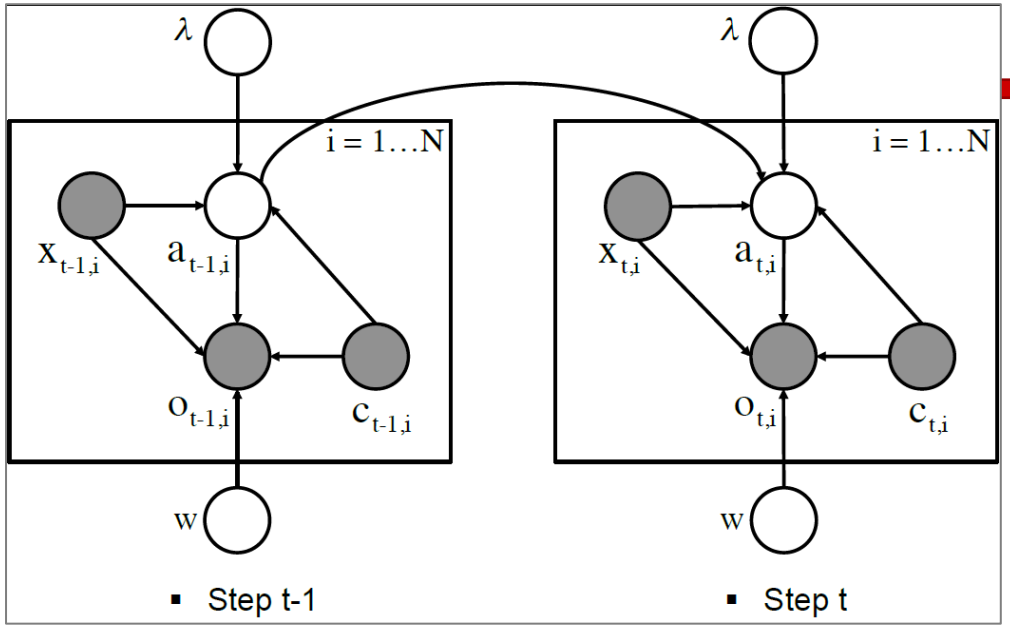
Optimal Patrol Strategy (CAPTURE)

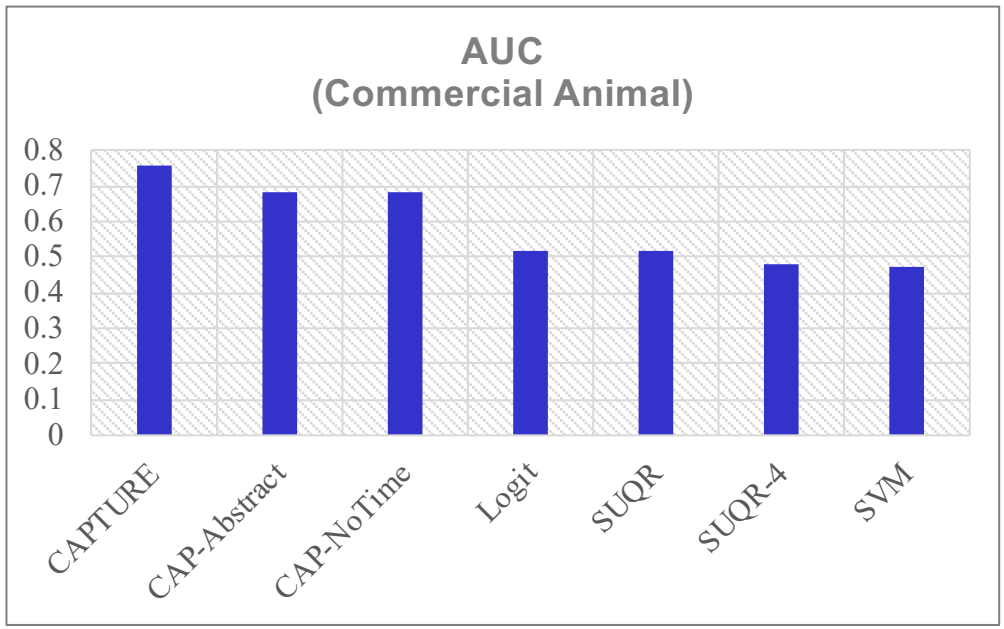


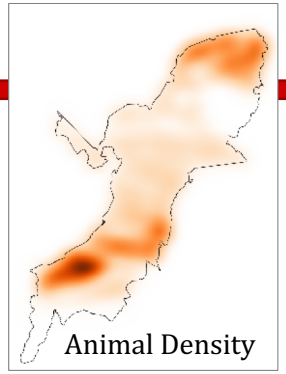
Attack Probability (CAPTURE)

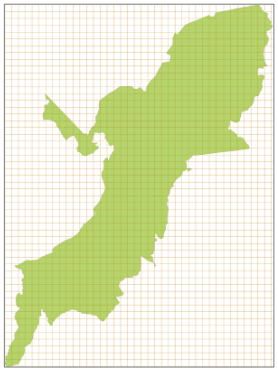
CAPTURE

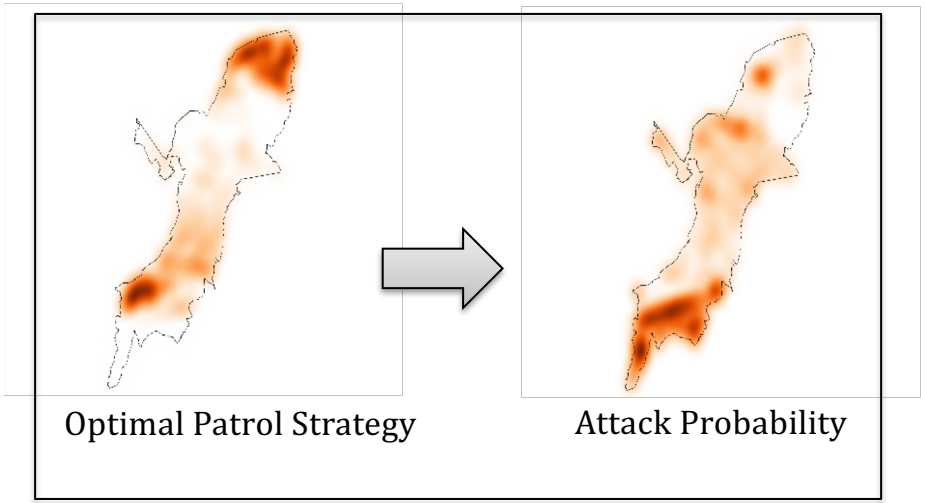
A New Predictive Anti-Poaching Tool for Wildlife Protection











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