AI and Multiagent Systems Research for Social Impact

Public Safety and Security

Conservation

Public Health
Viewing Social Problems as Multiagent Systems

Key research challenge across problem areas:

Optimize Our Limited Intervention Resources when Interacting with Other Agents

Multiagent Systems Reasoning:
Game Theory, Networks
Public Safety and Security
Optimizing Limited Intervention (Security) Resources

- Game Theory for security resource optimization
- Real-world: US Coast Guard, US Federal Air Marshals Service…

Date: 12/3/2019
Conservation/Wildlife Protection
Optimizing Limited Intervention (Ranger) Resources

Green Security Games

- Security games and adversary (poacher) behavior prediction
- Real-world: National parks in Uganda, Malaysia…
Games against Nature

- Social networks to enhance intervention, e.g., HIV information
- Real-world pilot tests: Homeless youth shelters in Los Angeles
Google Research Bangalore (Forthcoming)
Optimizing Limited Intervention Resources

Director, AI for Social Good

Public Health & Welfare
Conservation
Education

- New projects in public health, conservation, education
Common Themes
Interdisciplinary Partnerships, Multiagent Systems, Data-to-deployment pipeline

Date: 12/3/2019
Common Themes
Interdisciplinary Partnerships, Multiagent Systems, Data-to-deployment pipeline

- Field tests & deployment
- Prescriptive algorithm
  - Game theory Intervention
- Predictive model
  - Learning/Expert input
- Immersion
  - Data Collection

Date: 12/3/2019

[Logos of various organizations]
AI for Social Impact
Observations on Area of Research

Field tests & deployments because Social Impact is a key objective!

Encourage AI for Social Impact research: Value entire pipeline (contributions beyond algorithms in data collection, model, impact)
Outline: Overview of Past 12 Years of Research

- Public Safety & Security: Stackelberg Security Games
- Conservation/Wildlife Protection: Green Security Games
- Public Health: Influence maximization/Game against nature

- AAMAS, AAAI, IJCAI
- Real world evaluation
- PhD students & postdocs
Game Theory direct use for security resource optimization?
Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games

<table>
<thead>
<tr>
<th></th>
<th>Terminal #1</th>
<th>Terminal #2</th>
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<tbody>
<tr>
<td>Terminal #1</td>
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</tr>
<tr>
<td>Terminal #2</td>
<td>-5, 5</td>
<td>2, -1</td>
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</table>

Defender

Adversary
Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games

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</table>

Date: 12/3/2019
New Model: Stackelberg Security Games

**Stackelberg**: Defender commits to randomized strategy, adversary responds.
**Security game**: Played on targets, payoffs based on targets covered or not.
**Optimization**: Not 100% security; increase cost/uncertainty to attackers.

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<td>Terminal #2</td>
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</table>
ARMOR at LAX
Basic Security Game Operation [2007]

<table>
<thead>
<tr>
<th>Defender #1</th>
<th>Target #1</th>
<th>Target #2</th>
<th>Target #3</th>
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<tr>
<td></td>
<td>2, -1</td>
<td>-3, 4</td>
<td>-3, 4</td>
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<tr>
<td>Defender #2</td>
<td>-3, 3</td>
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<tr>
<td>Defender #3</td>
<td>….</td>
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</table>

Mixed Integer Program

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

Canine Team Schedule, July 28

<table>
<thead>
<tr>
<th>Term 1</th>
<th>Term 2</th>
<th>Term 3</th>
<th>Term 4</th>
<th>Term 5</th>
<th>Term 6</th>
<th>Term 7</th>
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<tbody>
<tr>
<td>8 AM</td>
<td>Team1</td>
<td></td>
<td>Team3</td>
<td>Team5</td>
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<tr>
<td>9 AM</td>
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<td>Team1</td>
<td>Team2</td>
<td></td>
<td>Team4</td>
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</tbody>
</table>

Date: 12/3/2019
Security Game MIP [2007]  
Payoffs Estimated From Previous Research

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

s.t.  
$$\sum_{i} x_i = 1$$

$$\sum_{j} q_j = 1$$

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

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<tr>
<th></th>
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<th>Target #2</th>
<th>Target #3</th>
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<td>-3, 4</td>
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<td>Defender #3</td>
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Maximize defender expected utility

Defender mixed strategy

Adversary response

Adversary best response

Date: 12/3/2019
SECURITY GAME PAYOFFS [2007]
Previous Research Provides Payoffs in Security Games

+ Handling Uncertainty

Maximize defender expected utility

\[
\max \sum_{i \in X} \sum_{j \in Q} R_{ij} x_i q_j
\]
**ARMOR:**
Optimizing Security Resource Allocation [2007]

First application: Computational game theory for operational security

January 2009

- **January 3rd**
  - Loaded 9/mm pistol
  - 16-handguns
  - 1000 rounds of ammo

- **January 9th**
  - Two unloaded shotguns

- **January 10th**
  - Loaded 22/cal rifle

- **January 12th**
  - Loaded 9/mm pistol

- **January 17th**
  - Loaded 9/mm pistol

- **January 22nd**
  - Unloaded 9/mm pistol

Date: 12/3/2019
ARMOR AIRPORT SECURITY: LAX [2008]
Congressional Subcommittee Hearings

Commendations
City of Los Angeles

Erroll Southers testimony
Congressional subcommittee

ARMOR...throws a digital cloak of invisibility....
## IRIS

**Federal Air Marshals Service [2009]**

1000 flights, 20 air marshals: $10^{41}$ combinations

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**Master**

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<th>...</th>
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<th>Attack 13</th>
<th>Attack 14</th>
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<th>Attack 18</th>
<th>Attack 19</th>
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**Slave (LP Duality Theory)**

- Best new pure strategy
- Next best new pure strategy
PROTECT: Port and Ferry Protection Patrols [2011] Using Marginals for Scale up

Boston

Los Angeles

New York

Meritorious Team Commendation from Commandant (US Coast Guard)

Date: 12/3/2019
Solving Problems: Overall Research Framework
End-to-End, Data to Deployment Pipeline

- Immersion: Data Collection
- Predictive model: Learning/Expert input
- Prescriptive algorithm: Game theory Intervention
- Field tests & deployment

Date: 12/3/2019
Global Presence of Security using Game Theory
Significant Real-World Evaluation Effort

Security Games superior in Optimizing Limited Security Resources
Vs
Human Schedulers/“simple random”
Field Evaluation of Schedule Quality

Improved Patrol Unpredictability & Coverage for Less Effort

Train patrols: Game theory outperformed expert humans schedule 90 officers
Field Tests Against Adversaries

Computational Game Theory in the Field

**Controlled**
- 21 days of patrol, identical conditions
- Game theory vs Baseline+Expert

**Not Controlled**

---

Date: 12/3/2019
Outline

Public Safety & Security: Stackelberg Security Games

Conservation/Wildlife Protection: Green Security Games

Public Health: Influence maximization/Game against nature

Dr Andy Plumptre
Conservation Biology
Poaching of Wildlife in Uganda
Limited Intervention (Ranger) Resources to Protect Forests

Snare or Trap

Wire snares
Adversary not fully strategic; multiple “bounded rational” poachers

Max defender utility
Defender mixed strategy

\[
\begin{align*}
\max_{x,q} & \sum_{i \in X} \sum_{j \in Q} R_{ij} x_i q_j \\
\text{s.t.} & \sum_{i} x_i = 1 \\
0 & \leq (a - \sum_{i \in X} x_i) \leq (1 - q_j) M
\end{align*}
\]
Learn adversary bounded rational response: At each grid location $i$

Ranger patrols: $X(i)$

Features: $F(i)$

Probability of finding snare in cell $i$

Machine Learning

$$\max_{x} \sum_{i \in X} g_i(x_i)$$

$$\text{s.t. } \sum_{i} x_i = 1$$

Max defender utility

Defender mixed strategy
Learning Adversary Model
12 Years of Past Poaching Data

Probability of snare Per 1 KM Grid Square

- Ranger patrol
- Animal density
- Distance to rivers / roads / villages
- Area habitat
- Area slope
- ...
Learning Adversary Model
Uncertainty in Observations

Probability of snare Per 1 KM Grid Square

- Ranger patrol
- Animal density
- Distance to rivers / roads / villages
- Area habitat
- Area slope
- ...

Record: No Attack (NEG)  Record: Attack (POS)

Walk more!
Adversary Modeling [2016]
Imperfect Crime Observation-aware Ensemble Model

Training: Filtered Datasets

Patrol Effort

Predict: Ensemble of Classifiers

Patrol Effort

Gholami
PAWS: Protection Assistant for Wildlife Security
Poacher Attack Prediction in the Lab

Poacher Behavior Prediction

Results from 2016

Date: 12/3/2019
PAWS:
Real-world Deployment 2016: First Trial

- Two 9-sq. km patrol areas
  - Where there were infrequent patrols
  - Where no previous hot spots

Date: 12/3/2019
PAWS Real-world Deployment
Two Hot Spots Predicted

- Poached Animals: Poached elephant
- Snaring: 1 elephant snare roll
- Snaring: 10 Antelope snares

<table>
<thead>
<tr>
<th>Historical Base Hit Rate</th>
<th>Our Hit Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average: 0.73</td>
<td>3</td>
</tr>
</tbody>
</table>

Date: 12/3/2019
PAWS Predicted High vs Low Risk Areas: 2 National Parks, 24 areas each, 6 months [2017]

Queen Elizabeth National Park

Murchison Falls National Park

Snares per patrolled sq. KM

Experiment group

High-risk

Low-risk

0.25

0.2

0.15

0.1

0.05

0

0.6

0.4

0.2

0

High-risk

Medium-risk

Low-risk

Date: 12/3/2019
PAWS Real-world Deployment
Cambodia: Srepok Wildlife Sanctuary [2018-2019]

Srepok Wildlife Sanctuary has been identified as the most suitable site for tiger reintroduction in Southeast Asia.
“@Milind: I am Super excited with the results. Let’s get this going on other countries too this year.”

Rohit Singh, WWF (2019)

521 snares/month our tests vs 101 snares/month 2018

Snares per patrolled sq. KM

Experiment Group

- High-risk
- Medium-risk
- Low-risk
Green Security Games: Around the Globe with SMART partnership [2019]

Protect Wildlife
800 National Parks Around the Globe

Also: Protect Forests, Fisheries…
Green Security Games: Integrating Real-Time Information in the Pipeline

Data Collection

Learn predictions with Historical Ground Truth Data

Prediction $g_i$

Prescription

$$\max_x \sum_{i \in x} g_i(x_i)$$

$s.t. \sum_i x_i = 1$

Field

Real-Time information

Date: 12/3/2019
Green Security Games: Integrating Real-Time “SPOT” Information [2018]

Goal: automatically find poachers
Drone Used to Inform Rangers [2019]

- $\text{Prob}(\text{ranger arrives}) = 0.3$ [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving
Drone Used to Inform Rangers [2019]

- $\text{Prob(ranger arrives)} = 0.3$  [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving
Drone Used to Inform Rangers [2019]

- $\text{Prob}(\text{ranger arrives}) = 0.3$ [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving
- Must be strategic in deceptive signaling
Strategic Signaling: Informational Advantage
Defender Knows Pure & Mixed Strategy

New Model: Stackelberg Security Games with Optimal Deceptive Signaling

- Poacher best interest to “believe signal” even if know 50% time defender is lying
- Theorem: Signaling reduces complexity of equilibrium computation
Strategic Signaling: Handling Detection Error
Exploit Informational Asymmetry to Mitigate Impact

Strategic signaling in presence of error in detecting adversaries

- Defender knows adversary detected or not; Attacker knows Prob (detection error)
- Signal (at random) when no adversary detection
Green Security Games Pipeline: Not Enough Data in Some Parks

- Not enough data
  - May not learn accurate enough adversary model
  - May lead to errors in planning patrols on targets

- **Game focused learning**
  - Maximizing learning accuracy ≠ Maximizing decision quality
  - Learn to maximize decision quality
Previous Stage-by-Stage Method: Make Prediction as Accurate as Possible Then Plan

Data Collection → Prediction $g_i$ → Prescription

Maximize accuracy in Adversary target values *estimates*

Plan patrol Coverage

Minimize $\sum_{i \in T} q_{\text{empirical}} \log \hat{q}$
Stage by Stage Method: Need to Focus on Important Targets

- **Data Collection**
- **Prediction** \( g_j \)
- **Prescription**
  \[
  \max_x \sum g_i(x_i) \\
  \text{s.t. } \sum x_i = 1
  \]
- **Field**

Maximize accuracy in Adversary target values *estimates*

Minimize \( \sum_{i \in T} q_{\text{empirical}} \log \hat{q} \)

Plan patrol Coverage

Two targets: Large effect Defender EU
Game-Focused Learning: Need to Focus on Important Targets

Maximize accuracy only of Important targets

Minimize $\sum_{i \in T} q_{\text{empirical}} \log \hat{q}$

Two targets: Large effect Defender EU

Plan patrol Coverage

Data Collection

Prediction $g_i$

Prescription $\max \sum g_i(x_i)$

$s.t. \sum x_i = 1$

Field
Game-Focused Learning: End-to-End Method

Maximize defender expected utility

\[ \sum (1 - p_i(\hat{q})) q_{\text{empirical}} \]
Previous Two-Stage Method: Gradient Descent

Max accuracy gradient descent:

\[
\frac{\partial \text{accuracy}}{\partial \text{weights}} = \frac{\partial \text{prediction}}{\partial \text{weights}} \frac{\partial \text{accuracy}}{\partial \text{prediction}}
\]
Game-Focused Learning: End-to-End Method

Game-focused gradient descent:

\[ \frac{\partial \text{obj}(\text{decision})}{\partial \text{weights}} = \frac{\partial \text{prediction}}{\partial \text{weights}} \cdot \frac{\partial \text{prediction}}{\partial \text{decision}} \cdot \frac{\partial \text{obj}(\text{decision})}{\partial \text{decision}} \]
Game-Focused Learning: 
End-to-End Method

- Focusing learning on important targets increases defender utility
Outline

Public Safety & Security: Stackelberg Security Games

Conservation/Wildlife Protection: Green Security Games

Public Health: Game against nature

Prof Eric Rice
Social Work
Public Health
Optimizing Limited Intervention (Social Worker) Resources

Preventing HIV in homeless youth: Rates of HIV 10 times housed population

- **Shelters**: Limited number of peer leaders to spread HIV information in social networks
- “Real” social networks gathered from observations in the field; not Facebook etc
Influence Maximization Background

- **Given:**
  - Social network Graph G
  - Choose K “peer leader” nodes

- **Objective:**
  - Maximize expected number of influenced nodes

- **Assumption: Independent cascade model of information spread**
Independent Cascade Model and Real-world Physical Social Networks

\[ P(A, B) = 0.4 \]

\[ \mu = 0.5 \]

\[ \mu \in [0.3, 0.7] \]
Robust, Dynamic Influence Maximization

- Worst case parameters: a zero-sum game against nature

  Algorithm
  Chooses policy, i.e.,
  Chooses Peer leaders

  vs

  Nature
  Chooses parameters
  $\mu, \sigma$

- Payoffs: (performance of algorithm)/OPT
HEALER Algorithm [2017]
Robust, Dynamic Influence Maximization

*Theorem:* Converge with approximation guarantees

- Equilibrium strategy despite exponential strategy spaces: Double oracle

<table>
<thead>
<tr>
<th>Influencer</th>
<th>Nature</th>
<th>Influencer’s oracle</th>
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<td>0.8, -0.8</td>
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<td>Policy #2</td>
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<tr>
<th>Nature’s oracle</th>
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<tr>
<td>Policy #2</td>
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<td>0.5, -0.5</td>
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<tr>
<td>Policy #3</td>
<td>0.6, -0.6</td>
<td>0.4, -0.4</td>
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</table>

Date: 12/3/2019
Challenge: Multi-step Policy

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<td>0.7, -0.7</td>
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K = 4
1st time step

K = 4
2nd time step

Date: 12/3/2019
HEALER: POMDP Model for Multi-Step Policy
Robust, Dynamic Influence Maximization

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<th>Policy</th>
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<td>0.6, -0.6</td>
<td>0.4, -0.4</td>
<td>0.7, -0.7</td>
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Choose nodes

Observation: Update propagation probability
Pilot Tests with HEALER with 170 Homeless Youth [2017]

Recruited youths:

<table>
<thead>
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<th>HEALER</th>
<th>HEALER++</th>
<th>DEGREE CENTRALITY</th>
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<td>62</td>
<td>56</td>
<td>55</td>
</tr>
</tbody>
</table>

12 peer leaders
Results: Pilot Studies [2017]

Data to Deployment Pipeline: Network Sampling to avoid Data Collection Bottleneck

Data collection costly

Sample 18%

Sampling from largest communities

New experiment With 60 homeless youth

12 peer leaders
Results: Pilot Studies with New Sampling Algorithm [2018]

Percent of non-Peer Leaders
- Informed
- Not Informed

Informed Non-Peer Leaders Who Started Testing for HIV
- Testing
- Non-Testing

Date: 12/3/2019
Continuing Research on HIV prevention [2019]

- Completing 900 youth study at three homeless shelters
Tuberculosis (TB): ~500,000 deaths/year, ~3M infected in India

- Patient in low resource communities: Non-adherence to TB Treatment
- Digital adherence tracking: Patients call phone #s on pill packs; many countries
- Predict adherence risk from phone call patterns? Intervene before patients miss dose
TB Treatment Adherence but Limited Resources: Intervening Selectively before patients miss doses

- Data Collect
  - Phone logs
- Predict high risk patients
  - RF or LSTM
- Prescription Constraint Top K
- Field

- 15K patients, 1.5M calls

everwell
Increasing TB Treatment Adherence: Intervening before patients miss doses [2019]

Data from State of Maharashtra, India

Best Model vs. Baseline: Prediction High Risk Patients

- True Positives: Baseline 107, Best Model 144 (+35%)
- False Positives: Baseline 120, Best Model 97 (-19%)

Date: 12/3/2019
Improving TB interventions
Decision-Focused vs Stage by Stage Methods

Decision focused learning improves TB interventions

Interventions: Decision-Focused Better

Stage by Stage | Decision Focused
---|---
0.4 | 0.5
0.42 | 0.48
0.44 | 0.46
0.46 | 0.44
0.48 | 0.42
0.5 | 0.4
Integrating with Everwell’s Platform

This work has a lot of potential to save lives.

Bill Thies
Co-founder, Everwell Health Solutions
Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks

- Worst case parameters: a zero-sum game against nature
- Fairness of coverage

Algorithm
Chooses K gatekeepers

vs

Nature
Chooses some gatekeepers to not participate
Childhood Obesity Prevention via Network Optimization

- **Childhood obesity:** Diabetes, stroke and heart disease
- **Early intervention with mothers:** Change diet/activity using social networks
- **Competitive influences in networks:** Add/remove edges for behavior change
Cross-cutting challenge: How to optimize limited intervention resources

- Public safety & security, conservation, public health

Unifying themes

- Multiagent systems reasoning
- Data to deployment

Research contributions:

- *Models, algorithms*: Stackelberg Security Games, game-focused learning
- *Beyond models and algorithms*...
Data to deployment perspective: Not just improving algorithms

Important to step out of the lab and into the field

Embrace interdisciplinary research -- social work, conservation

Lack of data is the norm, a feature; part of the project strategy

AI for Social Impact should be evaluated differently
Thank you!

Collaborate to realize AI’s tremendous potential to
Improving society & fighting social injustice

@MilindTambe_Ai
Game-focused learning approach

→ Goal of learning: *defender’s utility* as high as possible

→ Not accurate predictions; but predictions for best decision
Game-Focused Learning: Reduces Errors on Important Targets

Game-focused Two-stage Target Importance

Game-focused  Two-stage

Date: 12/3/2019