AI and Multiagent Systems for Social Good

MILIND TAMBE
Founding Co-director, Center for Artificial Intelligence in Society (CAIS)
University of Southern California
tambe@usc.edu

Co-Founder, Avata Intelligence
AI and Multiagent Systems Research for Social Good

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
Optimizing Limited Intervention (Security) Resources

Public Safety and Security
Stackelberg Security Games

- Game Theory for security resource optimization
- Real-world: US Coast Guard, US Federal Air Marshals Service…
Multiagent Systems
Optimizing Limited Intervention (Ranger) Resources

Conservation/Wildlife Protection: Green Security Games

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

- Social networks to enhance intervention, e.g., HIV information
- Real-world pilot tests: Homeless youth shelters in Los Angeles
Solving Problems: Overall Research Framework

Interdisciplinary Partnerships
Solving Problems: Overall Research Framework
Interdisciplinary Partnerships

Immersion
Data Collection

Predictive model
Learning/Expert input

Prescriptive algorithm
Game theory Intervention

Field tests & deployment

Date: 1/29/2019
Outline: Overview of Past 10 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

Date: 1/29/2019
11 July 2006: Mumbai

**TRAIN OF TERROR**

Mumbai continues to be the prime target for terrorist groups. It has borne the brunt of seven attacks in the past 13 years.

- **Explosive used**
  - High-quality explosives, mostly RDX
  - (Cyclone/Incendio
  - Metropolitan)

- **Quantity of explosive**
  - At least 5 kg per blast
  - Much easier packed into bags or tiffin boxes

- **Why attack the first class compartments?**
  - It is easier to enter a first class compartment at peak hour than a second class with a bag filled with up to 5 kg of explosives

- **Where were bombs placed?**
  - In the baggage racks where commuters keep their bags and tiffin boxes

- **How many bombers were there?**
  - At least 20, 2 for each train and a logistic team of 5 people

---

**WARN**

- JAN 13, 2006:
  - Saved from three youths in Mumbai
- JAN 23, 2006:
  - Powder and 2 kg of dynamite
- MAR 15, 2006:
  - Three terrorists in a car
- APR 14, 2006:
  - Three AK-47s and hand grenades found
- MAY 14, 2006:
  - Three AK-47s and hand grenades found

---

**Mumbai**

- **MAHARASHTRA**
- **NAGPUR**
- **MUMBAI**
- **NAIK**
- **MOLLEGAON**
- **NEHRANGABAD**
- **NASIK**

---

Date: 1/29/2019
Game Theory direct use for security resource optimization?

Erroll Southers

LAX Airport, Los Angeles

Glasgow: June 30, 2007

Date: 1/29/2019
Game Theory for Security Resource Optimization

New Model: Stackelberg Security Games

<table>
<thead>
<tr>
<th>Defender</th>
<th>Terminal #1</th>
<th>Terminal #2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terminal #1</td>
<td>4, -3</td>
<td>-1, 1</td>
</tr>
<tr>
<td>Terminal #2</td>
<td>-5, 5</td>
<td>2, -1</td>
</tr>
</tbody>
</table>
**Game Theory for Security Resource Optimization**

**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

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

**Date**: 1/29/2019
ARMOR at LAX
Basic Security Game Operation [2007]

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>
<th>Term 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 AM</td>
<td>Team1</td>
<td></td>
<td></td>
<td>Team3</td>
<td>Team5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 AM</td>
<td></td>
<td>Team1</td>
<td>Team2</td>
<td></td>
<td></td>
<td>Team4</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Security Game MIP [2007]

Maximize defender expected utility

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

s.t.
\[
\sum_i x_i = 1
\]
\[
\sum_{j \in Q} q_j = 1
\]
\[
0 \leq (a - \sum_{i \in X} C_{ij} x_i) \leq (1 - q_j) M
\]

Date: 1/29/2019
## SECURITY GAME PAYOFFS [2007]

Previous Research Provides Payoffs in Security Games

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

\[
\text{Maximize defender expected utility}
\]

\[
\text{max} \sum_{i \in X} \sum_{j \in Q} R_{ij} \times x_i \times q_j
\]

+ Handling Uncertainty

Date: 1/29/2019
First application: Computational game theory for operational security

- 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

Date: 1/29/2019
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….
Federal Air Marshals Service [2009]

Visiting Freedom Center: Home of Federal Air Marshals Service
Scale Up Difficulty [2009]

\[ x_i \quad \text{Defender mixed strategy} \]

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

\[
\text{s.t. } \sum_{i} x_i = 1, \sum_{j} q_j = 1
\]

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

1000 flights, 20 air marshals:

10^{41} \text{ combinations}

<table>
<thead>
<tr>
<th>Attack 1</th>
<th>Attack 2</th>
<th>Attack ...</th>
<th>Attack 1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>1, 2, 3 ..</td>
<td>5, -10</td>
<td>4, -8</td>
<td>...</td>
</tr>
<tr>
<td>1, 2, 4 ..</td>
<td>5, -10</td>
<td>4, -8</td>
<td>...</td>
</tr>
<tr>
<td>1, 3, 5 ..</td>
<td>5, -10</td>
<td>-9, 5</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>10^{41} \text{ rows}</td>
<td></td>
</tr>
</tbody>
</table>
**Theorem**: For $T$ targets, optimal solution of support set size $T+1$ always exists.

Small support set size: Most $x_i$ variables zero

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

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<th>Attack 2</th>
<th>Attack ...</th>
<th>Attack 1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,2,3...</td>
<td>5,10</td>
<td>4,0</td>
<td>...</td>
</tr>
<tr>
<td>1,2,4...</td>
<td>5,-10</td>
<td>4,-8</td>
<td>...</td>
</tr>
<tr>
<td>1,3,5...</td>
<td>5,10</td>
<td>9,5</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>-20,9</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>-20,9</td>
</tr>
</tbody>
</table>

$X_{123} = 0.0$

$X_{124} = 0.239$

$X_{135} = 0.0$

$X_{378} = 0.123$
**New Exact Algorithm for Scale up**

**Incremental strategy generation:** First for Stackelberg Security Games

### Master

<table>
<thead>
<tr>
<th></th>
<th>Attack 1</th>
<th>Attack 2</th>
<th>...</th>
<th>Attack 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,2,4</td>
<td>5, -10</td>
<td>4, -8</td>
<td>...</td>
<td>-20, 9</td>
</tr>
<tr>
<td>1,2,4</td>
<td>5, -10</td>
<td>4, -8</td>
<td>...</td>
<td>-20, 9</td>
</tr>
<tr>
<td>3,7,8</td>
<td>-8, 10</td>
<td>-8, 10</td>
<td>...</td>
<td>-8, 10</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td></td>
<td>...</td>
</tr>
</tbody>
</table>

### Slave (LP Duality Theory)

Best new pure strategy

**GLOBAL OPTIMAL**

1000 defender strategies

NOT $10^{41}$
IRIS: Deployed FAMS [2009-]

Significant change in FAMS operations

September 2011: Certificate of Appreciation (Federal Air Marshals)
PROTECT: Port and Ferry Protection Patrols [2011] Using Marginals for Scale up

Date: 1/29/2019
PROTECT: Ferry Protection Deployed [2013]
FERRIES: Mobile Resources & Moving Targets
Spatio-Temporal Security Games: Transition Graphs

Date: 1/29/2019
FERRIES: Mobile Resources & Moving Targets
Spatio-Temporal Security Games: Transition Graphs

Date: 1/29/2019
FERRIES: Mobile Resources & Moving Targets
Spatio-Temporal Security Games: Transition Graphs

Date: 1/29/2019

Diagram showing transition graphs for different resources and their movement over time.
FERRIES: Scale up Difficulties

Exponential $N^T$ routes: variables

<table>
<thead>
<tr>
<th></th>
<th>5 min</th>
<th>10 min</th>
<th>15 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>A, 5 min</td>
<td>A, 10 min</td>
<td>A, 15 min</td>
</tr>
<tr>
<td>B</td>
<td>B, 5 min</td>
<td>B, 10 min</td>
<td>B, 15 min</td>
</tr>
<tr>
<td>C</td>
<td>C, 5 min</td>
<td>C, 10 min</td>
<td>C, 15 min</td>
</tr>
</tbody>
</table>

Date: 1/29/2019

Ferry

Patroller

Exponential $N^T$ routes: variables
Theorem: **Marginals** enable scale-up with no solution quality loss
PROTECT: Port Protection Patrols [2013]  
Congressional Subcommittee Hearing

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

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

Date: 1/29/2019
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

Patrols Before PROTECT: Boston

Patrols After PROTECT: Boston

350% increase in defender expected utility
Field Evaluation of Schedule Quality

**FAMS: IRIS Outperformed expert human over six months**

Report: GAO-09-903T

**Train patrols:** Game theory outperformed expert humans schedule 90 officers

Date: 1/29/2019
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: 1/29/2019
New Directions in Stackelberg Security Games [2018]

- Threat Screening Games (AAAI16, IJCAI17, IJCAI18…)

- Cyber Security Games (IJCAI17, AAMAS18, CogSci18…)

Date: 1/29/2019
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

Date: 1/29/2019
Adversary not fully strategic; multiple “bounded rational” poachers

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

- **Ranger patrols:** $X(i)$
- **Features:** $F(i)$

Probability of finding snare in cell $i$

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

$$s.t. \sum_i x_i = 1$$

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
- ...

Date: 1/29/2019
Learning Adversary Model
Uncertainty in Observations

Record:
No Attack (NEG)

Walk more!

Record:
Attack (POS)

Ranger patrol
Animal density
Distance to rivers / roads / villages

Probability of snare Per 1 KM Grid Square

Area habitat
Area slope
...

Nguyen
Adversary Modeling [2016]
Imperfect Crime Observation-aware Ensemble Model

Training: Filtered Datasets

Predict: Ensemble of Classifiers

Patrol Effort

PatrolEffort = 0

PatrolEffort = 1

PatrolEffort = 2

Date: 1/29/2019
PAWS: Protection Assistant for Wildlife Security
Poacher Attack Prediction in the Lab

Poacher Behavior Prediction

Results from 2016

L&L Score
- Train Labels
- SVM
- Bagging Ensemble
- Our Best Model

Date: 1/29/2019
PAWS: Real-world Deployment 2016: First Trial

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

Date: 1/29/2019
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: 1/29/2019
PAWS Predicted High vs Low Risk Areas: 2 National Parks, 24 areas each, 6 months [2017]

Snares per patrolled sq. KM

Experiment group

High-risk
Low-risk

0.25
0.2
0.15
0.1
0.05
0

0
0.2
0.4
0.6

High-risk
Medium-risk
Low-risk

Date: 1/29/2019

Srepok Wildlife Sanctuary has been identified as the most suitable site for tiger reintroduction in Southeast Asia.

Date: 1/29/2019

@Milind: I am Super excited with the results. Let’s get this going on other countries too this year.“

521 snares/month our tests

101 snares/month 2018

Rohit Singh, WWF (2019)

Snares per patrolled sq. KM

High-risk

Medium-risk

Low-risk

Date: 1/29/2019
Green Security Games: Integrating Real-Time Information in the Pipeline

Learn predictions with Historical Ground Truth Data

Data Collection

Prediction $g_j$

Prescription
\[ \max_{x} \sum_{i \in x} g_i(x_i) \]
\[ s.t. \sum_{i} x_i = 1 \]

Field

Real-Time Information

Date: 1/29/2019
Green Security Games: Integrating Real-Time “SPOT” Information [2018]
Drone Used to Inform Rangers [2019]

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

$\text{Prob(ranger)} = 0.3$
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]

- $\text{Prob}(\text{ranger arrives}) = 0.3$ [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

Poacher best interest to “believe signal” even if know 50% time defender is lying
Green Security Games: Around the Globe with SMART partnership [2019]

Protect Wildlife 600 National Parks Around the Globe

Also: Protect Forests, Fisheries…
Outline

Public Safety & Security: Stackelberg Security Games

Conservation/Wildlife Protection: Green Security Games

Public Health: Game against nature

Prof Eric Rice
Social Work
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>Nature’s oracle</th>
<th>Influencer’s oracle</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Params #1</strong></td>
<td><strong>Policy #1</strong></td>
</tr>
<tr>
<td><strong>Policy #1</strong></td>
<td>0.8, -0.8</td>
</tr>
<tr>
<td><strong>Policy #2</strong></td>
<td>0.7, -0.7</td>
</tr>
<tr>
<td><strong>Policy #3</strong></td>
<td>0.6, -0.6</td>
</tr>
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<table>
<thead>
<tr>
<th>Nature</th>
<th><strong>Policy #1</strong></th>
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# Challenge: Multi-step Policy

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<td>0.4, -0.4</td>
<td>0.7, -0.7</td>
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</tbody>
</table>

**K = 4**

1\(^{st}\) time step

2\(^{nd}\) time step

Date: 1/29/2019
**HEALER: POMDP Model for Multi-Step Policy Robust, Dynamic Influence Maximization**

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<td>0.7, -0.7</td>
</tr>
</tbody>
</table>

**Observation:** Update propagation probability

**Action:** Choose nodes

**Hidden State:**

**POMDP Partitions:**

Yadav
Pilot Tests with HEALER with 170 Homeless Youth [2017]

Recruited youths:

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

12 peer leaders
Results: Pilot Studies [2017]

Practical Network Sampling: Avoid Data Collection Bottleneck

Data collection costly

Sample 18%

Sampling from largest communities

New experiment With 60 homeless youth

12 peer leaders

Date: 1/29/2019
Results: Pilot Studies with New Sampling Algorithm [2018]

Date: 1/29/2019

Wilder
Continuing Research on HIV prevention [2019]

- Completing 900 youth study at three homeless shelters
Public Health: Optimizing Limited Social Worker Resources Preventing Tuberculosis in India [2019]

_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
Public Health: Optimizing Limited Resources Preventing Tuberculosis in India [2019]

- Working jointly with Everwell Health Solutions & Microsoft Research India
- Everwell collaborates on software: Serves millions of TB patients in India, other countries
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

Date: 1/29/2019
Increasing TB Treatment Adherence: Intervening before patients miss doses

- Robust prediction of high risk patients, e.g., patient can't call on weekends
- A zero-sum game against nature

**Machine Learning**

Predict high risk patients

**Nature**

Adversarial perturb samples:
Reduce prediction accuracy
Increasing TB Treatment Adherence: Intervening before patients miss doses

- Predicting high risk patients: a zero-sum game against nature

- Result: Mixed strategy (randomization) over multiple predictors
Increasing TB Treatment Adherence: Intervening before patients miss doses [2019]

Data from State of Maharashtra, India

Best Model vs. Baseline: Prediction High Risk Patients

<table>
<thead>
<tr>
<th></th>
<th>True Positives</th>
<th>False Positives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>107</td>
<td>120</td>
</tr>
<tr>
<td>Best Model</td>
<td>144</td>
<td>97</td>
</tr>
</tbody>
</table>

+35% vs. -19%
Improving TB interventions

Decision-Focused vs Stage by Stage Methods

Decision focused learning improves TB interventions

AUC: In overall risk prediction
Decision-Focused  Worse

Interventions: Decision-Focused  Better

Date: 1/29/2019
Integrating with Everwell’s Platform

This work has a lot of potential to save lives.

Bill Thies
Co-founder, Everwell Health Solutions
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

Childhood Obesity Prevention at homeE (COPE)

Home Visitors Manual

Antelope Valley

Graph showing improvement over time for different methods.
Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks

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

**Algorithm**
Chooses K gatekeepers

**Nature**
Chooses some gatekeepers to not participate

1/29/2019
New Directions: Los Angeles
From an Angeleno [2019]

(AAMAS18)

Mayor Garcetti @ USC
New Directions: Mumbai
From a Mumbaikar [2019]

(AAAI18)

Chief Minister Maharashtra @ Mumbai
AI for Social Good
Key Lessons

Directing Multiagent Systems Research towards Social Good:
- Public safety & security, conservation, public health

Shared multiagent research challenges, solutions across problem areas:
- Challenge: Optimize limited intervention resources in interacting with others
- Solution: Computational game theory models/algorithms

Research contributions that arise from the domain:
- Models: Stackelberg Security Games/Green Security Games
- Algorithms: Incremental strategy generation, marginals, double oracle
Future: Multiagent Systems and AI Research for Social Good

Tremendous potential: Improving society & fighting social injustice

Vital to bring AI to those not benefiting from AI, e.g., global south

Embrace interdisciplinary research -- social work, conservation
Future Multiagent Systems and AI for Social Good in the FIELD

When working on AI for Societal Benefits:
- Important step out of lab & into the field
- Societal impact
- Actual problem for societal benefit?
- Model deficiencies for new research directions?
Thank you

Collaborators:

Sarit Kraus
Vince Conitzer
Eugene Vorobeychik
Andy Plumptre

USC Collaborators:

Eric Rice
Bistra Dilkina
Phebe Vayanos
Fernando Ordonez

Mentor: Barbara Grosz
Thank you for Inspiring Us
THANK YOU

@MilindTambe_AI

CAIS.USC.EDU