AI for Social Good: Key Techniques, Applications, and Results

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

Co-Founder, Avata Intelligence
Mission Statement: Advancing AI research driven by…

Grand Challenges of Social Work

- Ensure healthy development for all youth
- Close the health gap
- Stop family violence
- Advance long and productive lives
- End homelessness
- Achieve equal opportunity and justice

...
Overview of CAIS Project Areas

AI for Assisting Low Resource Communities

- Social networks: Spread HIV information, influence maximization
- Real-world pilot tests: Big improvements
Overview of CAIS Project Areas

AI for Public Safety and Security

- Game theory: security resource optimization
- Real-world: US Coast Guard, US Federal Air Marshals Service…
Overview of CAIS Project Areas

AI for Conservation, Protecting Endangered Wildlife

- Machine learning/planning: Predicting poaching spots, patrols
- Real-world: Uganda, South Asia…
Outline

- Introduction
- Low Resource Communities
- Public Safety and Security
- Wildlife Conservation
- AAMAS, AAAI, IJCAI: 2015-2017
  - PhD students/postdocs
Key Takeaways

- Significant potential: AI for low resource communities, emerging markets

- Not just applications:
  - Research challenges for ICAPS community from use-inspired research
  - Designing AI Planning and Scheduling systems in society:
    - Interpretability
    - Complementing human autonomy

- Methodological challenges:
  - Encourage interdisciplinary research: measures impact in society
Outline

- Introduction
- Low resource communities (homeless youth)
- Public Safety and Security
- Wildlife Conservation
AI Program: HEALER
Outline: HIV Information & Homeless Youth

- Domain of homeless youth and HIV information dissemination
- Real World Challenges in Influence Maximization
- Sequential Decision Making under Uncertainty
- Pilot Study
Influence Maximization Background

- **Input:**
  - Graph G
  - Influence Model I
  - Choose K nodes per time step
  - Number of time steps for influence spread T

- **Output:**
  - K nodes per time step maximizing expected # influenced nodes
Independent Cascade Model

\[ G = (V, E) \]

- Propagation Probability (for each edge)
Real World Challenges

- Uncertain network state
- Uncertainty in network structure
- Adaptive selection
Challenge 1: Uncertain Network State
Challenge 2: Uncertain Network Structure
Independent Cascade Model

\[ G = (V, E) \quad E = E_{\text{cert}} \cup E_{\text{uncert}} \]

- Propagation Probability (for each edge)

- Existence Probability (for uncertain edges only)
HIV Prevention Programs:
Using Social Networks to Spread HIV Information
Challenge: Adaptive selection in Uncertain Network

$K = 5$

$1^{st}$ time step
Have you heard?

Today's Agenda

1. Introduction
2. Sexual Health + Condoms
3. HIV/HCV/STI 101
4. Communication
5. Outreach
6. Leadership + Self Care

Wrap-up

With Robin Eric Jaih Amanda
Challenge: Adaptive selection in Uncertain Network

K = 5
2nd time step
Challenge 3: Adaptive selection

K = 5
3rd time step

NO LONGER A SINGLE SHOT DECISION PROBLEM
- NP-hard
- Not adaptive submodular
Outline: HIV Information & Homeless Youth

- Domain of homeless youth and HIV information dissemination
- Real World Challenges in Influence Maximization
- Sequential Decision Making under Uncertainty
- Pilot Study
POMDP Model: Create a Policy [2015]

- Homeless shelters – sequentially select nodes under uncertainty
  - Policy driven by observations about edges

```
<table>
<thead>
<tr>
<th>Action</th>
<th>Choose nodes</th>
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<tbody>
<tr>
<td>Observation: Which edges exist?</td>
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```

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POMDP SOLVER
Maximize Reward
```

```
World State: Actual node/edge state
```

Yadav
Optimal Policy at Real world scale: Why is it hard to solve?

- $2^{300}$ states
- $150C_6$ actions

Current offline and online POMDP solvers unable to scale
Real world scale: Why is it hard to solve?

Current algorithms fail to scale up

- Number of network nodes
- State of the art POMDP solvers
  - Offline solvers
  - Online solvers
POMDP Heuristics
Real world networks have community structure

Graph Partitioning
Graph Partitioning

- % of edges with endpoints in different clusters

Venice

Hollywood

Real World Networks
HEALER v1: Hierarchical Ensembling [2016]

ORIGINAL POMDP

HEALER

GRAPH PARTITION TOOL

Intermediate POMDP

Intermediate POMDP

Intermediate POMDP

Graph Sampling

Graph Sampling

Graph Sampling

Graph Sampling

Graph Sampling

Graph Sampling

Graph Sampling

GRAPH SAMPLER

Sampled POMDP

Sampled POMDP

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Sampled POMDP
HEALER v1: Partitioned Policies Combined for Final Result

INTERMEDIATE POMDP POLICY

Cross Community Edges Ignored
Intermediate POMDP
Intermediate POMDP

Expected Value

Value

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<td>7</td>
<td>3.4</td>
<td>10</td>
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Value

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<td>6</td>
<td>2</td>
<td>1</td>
<td>3.1</td>
<td>4.6</td>
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Expected Value

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<td>4.2</td>
<td>5</td>
<td>2.6</td>
<td>7</td>
<td>7.1</td>
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<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
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HEALER v2: Greedy Computation of POMDP Policy [2017]

Address Cross Community Edges but No Lookahead

Select Next Set of Highest Gain Nodes For each Observation
Real Networks – Simulation Results [2016-2017]

![Bar chart showing indirect influence for Venice and Hollywood.](image-url)

- **Venice**:
  - Degree
  - CR
  - PSINET
  - HEALER-1
  - HEALER-2

- **Hollywood**:
  - Degree
  - CR
  - PSINET
  - HEALER-1
  - HEALER-2
Robustness & Parameter Uncertainty

- HEALER: fixed propagation and existence probability

- Assume ranges of values, e.g., $U(A,B)$ is in $[0.4, 0.8]$

- Want policies robust to different possible values of $P(A,B)$ and $U(A,B)$
Robustness & Parameter Uncertainty

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

Nature
Chooses parameters P(A,B) and U(A,B)

Algorithm
Chooses policy in POMDP state-action space

- Payoffs: (performance of algorithm)/OPT
HEALER++ Algorithm [2017]

- Computes an equilibrium strategy for this game
- Exponentially large strategy space: incremental generation, double oracle
- Equilibrium: Under some conditions, provide approx. guarantees

<table>
<thead>
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<th>Nature</th>
<th>Nature’s oracle</th>
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<tr>
<td>Influencer</td>
<td>Influencer’s oracle</td>
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<tr>
<th></th>
<th>Params #1</th>
<th>Params #2</th>
<th>Params #3</th>
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<tbody>
<tr>
<td>Policy #1</td>
<td>0.8, -0.8</td>
<td>0.3, -0.3</td>
<td>0.4, -0.4</td>
</tr>
<tr>
<td>Policy #2</td>
<td>0.7, -0.7</td>
<td>0.5, -0.5</td>
<td>0.6, -0.6</td>
</tr>
<tr>
<td>Policy #3</td>
<td>0.6, -0.6</td>
<td>0.4, -0.4</td>
<td>0.7, -0.7</td>
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<td>0.4, -0.4</td>
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</tbody>
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Real networks - robustness

Worst case % of optimal influence

Venice

Hollywood

- HEALER++
- HEALER
Outline: HIV Information & Homeless Youth

- Domain of homeless youth and HIV information dissemination
- Real World Challenges in Influence Maximization
- Sequential Decision Making under Uncertainty
- Pilot Study
Pilot Tests
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>

Preliminary network —> HEALER
Bring 4 youth for training, get edge data —> HEALER
Bring 4 youth for training, get edge data —> HEALER
Bring 4 youth for training
Safe Place for Youth

- Collaborating with Safe Place for Youth (SPY)
Safe Place for Youth

- Collaborating with Safe Place for Youth (SPY)
Results: Pilot Studies

Percent of non-Peer Leaders

- Informed
- Not Informed

Informed Non-Peer Leaders Who Started Testing for HIV

- Testing
- Non-Testing
Analysis: Pilot Studies

1/5/19

% of edges between peer leaders

% Coverage of communities in 1st stage

HEALER

HEALER++

Degree

HEALER

HEALER++

Degree
AI Program: HEALER
Next Steps

- 900 youth study begun at three locations in Los Angeles
  - 300 enrolled in HEALER/HEALER++
  - 300 enrolled in no condition
  - 300 in Degree centrality

“Picking youth as peer leaders was changing their self esteem and the sense of confidence that they could be an agent for positive change....”

Eric Rice
Overview of CAIS Project Areas

AI for Assisting Low Resource Communities

- Substance abuse, suicide prevention…
- Modeling gang violence, matching homeless and homes…
Outline

- Introduction
- HIV Information among homeless youth
- Public Safety and Security
- Wildlife Conservation
Optimizing Security Resource Allocation [2007]

ARMOR: Assigning Limited Security Resources

Airports

Canine patrol at LAX (ARMOR)

2007
AI-based DECISION AIDS TO ASSIST IN SECURITY
Model: Stackelberg Security Games

Set of targets, payoffs based on targets covered or not…

**Stackelberg**: Defender commits to randomized strategy, adversary responds

**Security optimization**: Not 100% security; increase cost/uncertainty to attackers

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

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<tr>
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<th>Terminal #2</th>
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<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>
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</table>
### BASIC SECURITY GAME OPERATION [2007]

#### Mixed Integer Program

<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>
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<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></td>
<td>Team4</td>
</tr>
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<td>...</td>
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**Pr (Canine patrol, 8 AM @ Terminals 2, 5, 6) = 0.17**
SECURITY GAME MIP [2007]

\[
\begin{align*}
\text{Maximize defender expected utility} \\
\max \quad & \sum_{i \in X} \sum_{j \in Q} R_{ij} \times x_i \times q_j \\
\text{s.t.} \quad & \sum_i x_i = 1 \\
& \sum_{j \in Q} q_j = 1 \\
& 0 \leq (a \ - \sum_{i \in X} C_{ij} x_i) \leq (1 - q_j) M
\end{align*}
\]

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

Maximize defender expected utility

Defender mixed strategy

Adversary response

Adversary best response
Visiting TSA Freedom Center
Security Game Deployments [2009]

Airports

Air Marshals

2007 2009
Security Game Deployments

Security Games

- Airports (2007)
- Air Marshals (2009)
- Ports (2011)
PROTECT: Ferry Protection Deployed [2013-]
LA Sheriff’s Department & Evaluation [2014]

Fare Evasion

Ticketless Travelers Caught

- Game theory vs Previous Method

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

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

Report: GAO-09-903T

"Mock attacker" team analysis

PRE- to POST-PROTECT: “Deterrence” Improved
Game Theory for Security

Congressional Subcommittee hearings

LAX 2008  Air Marshals 2012  USCG 2013
Global presence of Security using Game Theory [2015-2017]
Avata Intelligence

Operational Efficiency Through AI

Los Angeles Unified School District Police
Glendale PD
Los Angeles Sheriff’s Department
University of Southern California
US Coast Guard
RAND Corporation
Threat Screening Games (TSG) [2016-2017]

- TSA: ~640 million passengers per year; “TSA Pre”
- New concept: More passenger categories using flight & risk level
- TSG: Tailor screening to categories, balance efficiency & effectiveness
- Extend to cybersecurity
Security Games in Cyberdefense: New MURI Project [2017-]

Realizing Cyber Inception:
Towards a Science of Personalized Deception for Cyber Defense

University of Southern California
Carnegie Mellon University
University of Texas El Paso
Arizona State University
North Carolina State University
University of North Carolina Chapel Hill
Green Security Games
Protecting Forests, Fisheries, Rivers [2015-2017]

FOREST PROTECTION

FISHERY PROTECTION

RIVER POLLUTION PREVENTION
Outline

- Introduction
- HIV Information among homeless youth
- Public Safety and Security
- Wildlife Conservation
What Might We Lose?

Murchison Falls National Park, Uganda
Protecting Wildlife in Uganda
PAWS: Protection Assistant for Wildlife Security [2016]

Massive forests (1000 sq miles) to protect, limited security resources:

- Generate “intelligently” randomized patrols
- Learn adversary models

Patrol boat in Bangladesh at Global Tiger Conference, 2014

Patrol with Rangers, Indonesia Trip with WWF, 2015
PAWS: Applying AI for protecting wildlife

Game Theory + Poacher Behavior Prediction

- Learn from crime data
- Game Theory calculate randomized patrols
- Poachers attack targets
- Patrollers execute patrols

PAWS: Applying AI for protecting wildlife

Fang
PAWS Patrols in the Field [2016]

Early Trials in Uganda and Malaysia

Important Lesson: Geography!

Uganda  Andrew Lemieux  Malaysia  Panthera
PAWS: Protection Assistant for Wildlife Security [2016]

Game Theory + Poacher Behavior Prediction + Forest Street Map
PAWS: Preliminary Evaluation

Human Activity Sign/km

- Previous Patrol: 0.57
- PAWS Patrol: 0.86

Fang
PAWS: Applying AI for protecting wildlife

Game Theory + Poacher Behavior Prediction

Predicting Poaching from Past Crime Data

Learn from crime data

Game Theory calculate randomized patrols

Patrollers execute patrols

Poachers attack targets

Nguyen
PAWS: Applying AI for protecting wildlife

Poacher Behavior Prediction

Predicting Poaching from Past Crime Data
Poacher behavior prediction [2016]

Data from Queen Elizabeth National Park, Uganda

Number of poaching attacks over 12 years: ~1000

How likely is an attack on a grid Square?

- Ranger patrol frequency
- Animal density
- Distance to rivers / roads
- Area habitat
- Area slope
- ...
Initial Attempt Behavioral Game Theory Models: Dynamic Bayes Net

Adversary’s probability of choosing target \( j \) is:

\[
e^{SEU_{\text{adversary}}(x,j)} \frac{1}{\sum_{j'=1}^{M} e^{SEU_{\text{adversary}}(x,j')}}
\]

Lack of sufficient data over the entire park
Poacher Behavior Prediction [2017]

Poacher Behavior Prediction

Ensemble of Decision Trees

Classifier 1

Classifier 2

Classifier 3

Majority

0

1

1

1
Feature Boosting: BoostIT Motivation

- Attacks seen in proximity of predictions
  - Add new feature “proximity of predictions”

Observed Attack
Prediction

- Observed Attack
- Prediction
Boost Decision Tree Ensembles with Behavioral Game Theory Models

- Boost in “heavily monitored” regions of the park:
  - Improve accuracy
  - Learn local poachers’ behavior; distinct parameters

---

**Diagram:**
- Classifier 1: Majority
- Classifier 2: Decision Tree
- Classifier 3: Behavioral model

---

Gholami
Nguyen
Poacher Attack Prediction [2017]

Poacher Behavior Prediction

Results from 2015
Real-world Deployment (1 month)

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

1/5/19
Real-world Deployment: (1 month)
Real-world Deployment: Results

- Two 9 sq KM patrol areas: Predicted hot spots with infrequent patrols
- Trespassing: 19 signs of litter etc.
- Snaring: 1 active snare
- Poached Animals: Poached elephant
- Snaring: 1 elephant snare roll
- Snaring: 10 Antelope snares

Hit rates (per month)
- Ours outperforms 91% of months

<table>
<thead>
<tr>
<th>Historical Base Hit Rate</th>
<th>Our Hit Rate</th>
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<tr>
<td>Average: 0.73</td>
<td>3</td>
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Real-world Deployment: Field Test 2 (6 months) [2017]

- 2 experiment groups (27 areas of 9 sq KM each)
  - 1:HIGH >= 50% attack prediction rate
    - 5 areas
  - 2: LOW < 50% attack prediction rate
    - 22 areas
Real-world Deployment: Field Test 2 (6 months) [2017]

- **Catch Per Unit Effort (CPUE)**
  - Unit Effort = km walked
  - Historical CPUE: 0.04
Field Test Side Effects:
Queen Elizabeth National Park

- Rangers followed poachers’ trail; ambushed camp
  - Arrested one (of 7) poachers
  - Confiscated 10 wire snares, cooking pot, hippo meat, timber harvesting tools.

- Pursuit of poachers
- Signs of road building, fires, illegal fishing
Next Steps

- Deployments in other parks
  - Murchison Falls National Park, Uganda (WCS); Cambodia (WWF)
  - Inclusion for general deployment worldwide
Green Security Games: Patrolling From the Sky [2017 ongoing]

UAV Patrolling: cheaper and more flexible

Credit: Arvind Iyer, AirShepherd

Credit: Liz Bondi
Green Security Games: Strategic Signaling in Security Games

UAV Patrolling: cheaper and more flexible

Strategically decide to send warning signals or keep silent (Signaling in security games: Xu et al. ‘15, ‘16)
New Challenges in Wildlife Patrolling: Surveillance of Current Patrol Location

Sometimes the poachers monitor our movement. Once they have monitored you, they know that, "Ah! He has gone. We are now free to enter [the park]."

⎯⎯⎯

Dennis Ng, Ranger at QENP

Ongoing Research: maximize entropy of patrolling routes

Def Utility in Security Games with Simple Scheduling Constraints
AI for Social Good

- IRIS Federal Air Marshals
- DARMS
- LA Metro
- Armorway
- ARMOR Airport Protection
- Border Patrol
- Armor-Fish
- Pollution Prevention
- Drug Design
- Forest Protection
- Coral Reef Protection
- PAWS Wildlife Protection

STREETS
Key Takeaways

- Significant potential: AI for low resource communities, emerging markets

- Not just applications:
  - Research challenges for ICAPS community from use-inspired research
  - Designing AI Planning and Scheduling systems in society:
    - Interpretability
    - Complementing human autonomy

- Methodological challenges:
  - Encourage interdisciplinary research: measures impact in society
THANK YOU

CAIS.USC.EDU

tambe@usc.edu
Lesson: Evaluating Deployed Security Systems is Not Easy
Ask the Right Questions!

Right Question: Optimized Use of Limited Security Resources?

NOT: How do you know this works? Is this the right boat?

Are Security Games superior to Humans/”simple random”
NOT: Is this the absolute best feasible

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<td>Compare real schedule</td>
<td>“Mock attackers”</td>
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<td>Human subject adversaries</td>
<td>Scheduling competition</td>
<td>Capture rates of real adversaries</td>
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<td>Expert evaluation</td>
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Deployment Lessons: Human Side of Security Games

From researcher side:

- **Humility is key; domain expertise is valued** ("Forest is a circle")
- **Carving out the right level of autonomy** ("turning us into robots")

From organization side:

- **Champion on the inside** ("Some connections never made")
- **Sympathetic to game theory even better** ("value of Stackelberg")
  - "Was Stackelberg a Nazi?"
  - (Stackelberg is Nash)

Interaction researcher-organization:

- **Immersion: opens our eyes; builds up trust over time** ("LASD")
Deployment Lessons: Software Side of Security Games

- Adhering to current practices
  - Similar to current methods including cosmetics (e.g., for FAMS)
  - Tweaking interface/display

- Ease of incorporation
  - Minimize infrastructure changes, e.g., same input/output

- Error checking
  - Give user tools to verify your solution
  - Highlight anomalies
Breakthrough research may be lost on something trivial (TSA)

e.g.,

- Initially truncated real numbers
- Users assumed inaccuracy
- Simple design issue lead to critical problems
…And the Past

“…prize every invention of science made for the benefit of all”
Real-world Deployment: Field Test 2 (6 months)

- Catch Per Unit Effort (CPUE)
  - Unit Effort = km walked
  - Historical CPUE: 0.04
On-Going Experiments: Queen Elizabeth National Park

- Red: Group 1 (highest attack prediction rate)
- Yellow: Group 2
- Green: Group 3
Game Theory for Security

Game Theory in the Field

Ticketless Travelers Caught

- Game theory vs Previous Method

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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**
AI-based DECISION AIDS TO ASSIST IN SECURITY

Airports

2007

Air Marshals

2009
AI-based DECISION AIDS TO ASSIST IN SECURITY

Game Theory

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<tr>
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<th>Paper</th>
<th>Rock</th>
<th>Scissors</th>
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<tr>
<td>Paper</td>
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<td>1, -1</td>
<td>-1, 1</td>
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<td>Rock</td>
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