AI for Public Health & Conservation: Learning & Planning in the Data to Deployment Pipeline

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AI & Multiagent Systems Research for Social Impact

Public Health

Conservation

Public Safety and Security
Key Research Challenge

Optimize Our Limited Intervention Resources
Optimizing Limited Intervention Resources

- **Public Health**
  - Social Networks & Bandits

- **Conservation**
  - Green security games

- **Public Safety & Security**
  - Stackelberg security games

Date: 11/19/2020
Google Research Bangalore
AI for Social Good

Public Health

Conservation
Three Common Themes
Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships

- Social networks
- Game theory

**Immersion**
Data Collection

**Predictive model**
Learning/Expert input

**Prescriptive algorithm**
Multiagent Reasoning Intervention

**Field tests & deployment**

Date: 11/19/2020
Three Common Themes
Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships

Field test & deployment: Social impact is a key objective

Lack of data is a norm: Must be part of project strategy

Immersion
Data Collection

Predictive model
Learning/Expert input

Prescriptive algorithm
Multiagent Reasoning Intervention

Field tests & deployment
Three Common Themes
Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships

Empower non-profits to use AI tools; avoid being gatekeepers to AI4SI technology
Outline

Public Health

- Information dissemination & behavior change: Social networks
- Health program adherence: ML & Bandits
- COVID-19: Agent-based modeling

Conservation

- Cover papers from 2017-now [AAMAS, AAAI, IJCAI, NeurIPS…]
- PhD students & postdocs highlighted
Information dissemination & behavior change
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” face-to-face interactions; not Facebook etc
Influence Maximization in Social Networks

- **Given:**
  - Social network Graph G
  - Choose K “peer leader” nodes
  - Assume: Independent cascade model of information spread

- **Objective:**
  - Maximize expected number of influenced nodes
Influence Maximization in Social Networks
Three Key Challenges Combined Together

➢ Uncertainty in propagation probability over edges

➢ Multi-step dynamic policies to handle peer leader “no shows”

➢ Unknown social network, limited query budget to SAMPLE network
Challenge 1: Uncertainty in Real-world Physical Social Networks

\[ P(C, D) = 0.4 \]

\[ \mu = 0.5 \]

\[ \mu \in [0.3, 0.7] \]
Robust Influence Maximization
(AAMAS 2017)

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

\[
\max_{x \in \Delta^{|P|}} \min_{\mu, \sigma} \sum_{x_p} \left( \frac{\text{Outcome}(p)}{OPT(\mu, \sigma)} \right)
\]

**Algorithm**
Choose Peer Leaders \( p \in P \) generating mixed strategy "\( x \in \Delta^{|P|} \)"

**Nature**
Chooses parameters \( \mu, \sigma \)
HEALER Algorithm
Robust Influence Maximization
(AAMAS 2017)

Theorem: Converge with approximation guarantees

- Equilibrium strategy despite exponential strategy spaces: Double oracle

<table>
<thead>
<tr>
<th>Nature</th>
<th>Influencer’s oracle</th>
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<tbody>
<tr>
<td></td>
<td><img src="image1.png" alt="Nature's oracle" /></td>
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<table>
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<tr>
<th>Policy</th>
<th>Params #1</th>
<th>Params #2</th>
<th>Params #3</th>
</tr>
</thead>
<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>
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Date: 11/19/2020
Challenge 2: POMDPs for Multi-step Policy
(AAMAS 2018a)

K = 4
1st time step

1st time step

K = 4
2nd time step

HIDDEN STATE

Action
Choose nodes

POMDP Policy

Observation: Node presence

Partition POMDPs: Exploit community structure

Date: 11/19/2020
Challenge 3: Sampling to avoid Data Collection Bottleneck (AAAI 2018)

Data collection costly

Sample 20%

Sampling Algorithm:
Sample node randomly & estimate size of its community; Choose seeds from largest K communities

Theorem: For community-structured graphs(*), sampling algorithm obtains a constant-factor approximation to the optimal influence spread using polylog(n) queries.

Input: total number of nodes, \( n \)

Query upto query budget

Output \( K \) peer leader nodes to spread influence

Perform similar to \( OPT \), best influence spread with full network

(*) Community structured: drawn from a stochastic block model
“Sampling-HEALER”
Pilot tests with 230 Homeless Youth
*(IJCAI 2018)*

<table>
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<tr>
<th>Sampling HEALER (Sampled Network)</th>
<th>HEALER (Full Network)</th>
<th>HEALER+ (Full Network)</th>
<th>DEGREE CENTRALITY (Full Network)</th>
</tr>
</thead>
<tbody>
<tr>
<td>60 youth</td>
<td>62 youth</td>
<td>56 youth</td>
<td>55 youth</td>
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Date: 11/19/2020
Results: Pilot Studies

![Graph showing percent of non-Peer Leaders](chart.png)

Date: 11/19/2020
Results of 750 Youth Study [with Prof. Eric Rice]
Actual Change in Behavior?
(Under submission)

First large-scale application of influence maximization for public health

Reduction in condomless anal sex (1 month)

Reduction in condomless anal sex (3 months)

Percent reduction

SAMPLING HEALER
Degree centrality
Control
Results of 750 Youth Study [with Prof. Eric Rice]

Reduction in condomless vaginal sex (3 months)

- **SAMPLING HEALER**
- **Degree centrality**
- **Control**
What our collaborators are saying:
Next steps: Data to Deployment Pipeline Using an RL agent?
(with B. Ravindran & team, AAMAS 2020)

**Network Family** | **Improve %**
--- | ---
Rural | 23.76
Animal | 26.6
Retweet | 19.7
Homeless | 7.91
Robust graph covering with gatekeepers, maximize worst case coverage

Disparity in coverage across racial groups

Maxmin fairness: \[ \min_{c \in C} u_c(A) \geq \gamma \]

Diversity constraints: \[ u_c(A) \geq U_c \]

\( \gamma \): Max of minimum utility for any community

\( U_c \): Utility if # gatekeepers allocated proportional to size of community
Outline

Public Health

- Information dissemination & behavior change: Social networks
- Health program adherence: Passive via ML vs Active via bandits
- COVID-19: Agent-based modeling

Conservation
Health Program Adherence
Maternal & Child Care in India
(Under submission)

India: Woman dies in childbirth every 15 min; 4 of 10 children too thin/short

- ARMMAN: 18 Million women enrolled, 160000 health workers…
- mMitra: Weekly call to new/expectant moms; friendly 3 minute messages about health
- mMitra: Significant benefits shown; 2.2 million women enrolled
- Unfortunately, significant fraction low-listeners or drop-outs
Passive Adherence Monitoring
Maternal & Child Care in India
(with B Ravindran IIT Madras)

Predict beneficiaries likely to drop out: Allows ARMMAN to focus intervention

- Neural networks for prediction: Extensive tests with past data
- Results of pilot with 18000 beneficiaries: High precision, recall, accuracy

- Prediction software deployed: helps 300,000 beneficiaries in mMitra

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ARMMAN Pilot

- 18000 Beneficiaries
- Nov & Dec 2019
- Test: Jan-April 2020

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![Graph showing F1, Recall, and Precision metrics for pilot prediction of beneficiaries at high risk of dropoff.]

- F1: High
- Recall: High
- Precision: High

---

![Diagram illustrating correct predictions and incorrect predictions of beneficiaries at high risk of dropoff.]
Passive Adherence Monitoring
Preventing Tuberculosis in India
(KDD 2019)

Tuberculosis (TB): ~500,000 deaths/year, ~3M infected in India

- Non-adherence to TB Treatment: Digital adherence tracking via daily phone calls
- Intervene before patients miss dose
- Predict adherence risk from phone call patterns?
- Results from Mumbai, India: 15,000 patients, 1.5 million phone calls

![Graph showing prediction high risk patients]

**Prediction High Risk Patients**

- True Positives
  - Baseline: 107
  - Best Model: 144
  +35%

- False Positives
  - Baseline: 120
  - Best Model: 97
  -19%
Intervention Reasoning: Active Adherence Monitoring

- Immersion
  - Data Collection
- Predictive model
  - Learning
- Prescriptive algorithm
  - Multiagent Reasoning Intervention
- Field tests & deployment
Intervention Scheduling with Scarce Data: Active Adherence Monitoring
(NeurIPS 2020)

**Health worker intervention**

Call patients: Track, improve adherence

**Challenge:**
- Large number of patients (N)
- Which ‘k’ patients to call?

**Approach:**
- Adherence Restless Bandits

Photo Credit: IntraHealth International (CC BY-NC-SA 3.0 via https://www.intrahealth.org/)
Intervention Scheduling with Scarce Data: Adherence Restless Bandits (A-RMAB) (NeurlIPS 2020)

Restless multiarmed bandits (RMAB)

Adherence RMAB (A-RMAB):
- Each arm (patient): binary latent state \{0, 1\}
- 0 = not-adhering; 1 = adhering

Patient state may be not observed:
- Belief state (i.e., probability) of adherence
Intervention Scheduling with Scarce Data: Adherence Restless Bandits (A-RMAB)

**When arm not played**
- No observation
- Instead, compute belief of adherence

**When arm is played**
- Observe current state
- Higher chance of adhering next round

Could convert into a giant POMDP & solve: but inefficient
Adherence Restless Bandits (A-RMAB): Whittle Index

- **Performance guarantee requires A-RMAB to be indexable**

  **Theorem 1:** A-RMAB Indexable if threshold policies are optimal.

- **Threshold policies: Forward Threshold**

  Call $\rightarrow$ Belief of adherence below threshold $\rightarrow$ Call

- **Exploiting threshold policies allow for a fast algorithm**
Intervention Scheduling with Scarce Data: Adherence Restless Bandits (A-RMAB)

- Orders of magnitude speedup with no solution quality loss
- ORANGE = Best baseline
- Blue = Our model
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- COVID-19: Agent-based modeling

Conservation
COVID-19: Agent-based Simulation Model
(Proceedings National Academy of Sciences, 2020)

Agent-based model:
- Families
- Co-morbidities
- Age
- Testing
- Contact tracing
COVID Testing Policy: Accuracy vs Ease

*(Science Advances, 2020)*

- Range of tests entering market, varying sensitivity/cost: Quantity vs Quality?
  - qRT-PCR ("gold standard"): Detect viral concentration of $10^3$/mL, $50-100
  - RT-LAMP: $10^5$/mL, $5-30
  - Antigen strip ("Less sensitive"): $10^6$/mL, $3-5

Test sensitivity is secondary to turnaround time & frequency for COVID-19 surveillance

- Less sensitive; Cheap & fast turnaround
- More sensitive; Costly & slow turnaround

<table>
<thead>
<tr>
<th>Total infections</th>
<th>Total infections</th>
<th>Total infections</th>
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<tbody>
<tr>
<td>1.00E+00</td>
<td>1.00E+04</td>
<td>1.00E+06</td>
</tr>
<tr>
<td>1.00E+02</td>
<td>1.00E+04</td>
<td>1.00E+06</td>
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<td>1.00E+06</td>
<td>1.00E+04</td>
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Every 3 days

(1 day delay)

Every 3 days

Every 3 days

Every 5 days
COVID Testing Policy: Impact

- WHO guidance reference
- Covered in NYT, WaPo, Time, The Atlantic, The Hill, etc
- Allowed epi collaborators to advocate to FDA/CDC
Conservation

- Protect wildlife, forests, fisheries: Game-focused learning
- Integrating real time data for protection: Signaling games
Protecting Conservation Areas: Green Security Games
(IJCAI 2015)

Snare or Trap

Wire snares

Date: 11/19/2020
From Stackelberg Security Games to Green Security Games
(IJCAI 2015)

- Stackelberg security games (SSG)
- With boundedly rational poachers
- Learn adversary response model at targets “i”

<table>
<thead>
<tr>
<th></th>
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<th>Area2</th>
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<tbody>
<tr>
<td>Area1</td>
<td>4, -3</td>
<td>-1, 1</td>
</tr>
<tr>
<td>Area2</td>
<td>-5, 5</td>
<td>2, -1</td>
</tr>
</tbody>
</table>
Learning Adversary Response Model: Uncertainty in Observations

Ranger patrol
Animal density
Distance to rivers / roads / villages

Probability of snare Per 1 KM Grid Square

Area habitat
Area slope

Training: Filtered Datasets

<table>
<thead>
<tr>
<th>Patrol Effort</th>
<th>Train Data</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>0 - 2000</td>
</tr>
<tr>
<td>1</td>
<td>-500 - 1500</td>
</tr>
<tr>
<td>2</td>
<td>-500 - 1500</td>
</tr>
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</table>

Predict: Ensemble of Classifiers

Patrol Effort

C0
C1
C2

Date: 11/19/2020
PAWS: First Pilot in the Field
(AAMAS 2017)

- Two 9-sq.km areas, infrequent patrols

- Poached elephant
- 1 elephant snare roll
- 10 Antelope snares
PAWS Predicted High vs Low Risk Areas: 3 National Parks, 24 areas each, 6 months
(ECML PKDD 2017, ICDE 2020)

Queen Elizabeth National Park

Murchison Falls National Park

Snares per patrolled sq. KM

0.3

0.2

0.1

0

Experiment group

High-risk

Low-risk

0.5

0

Experiment Group

High-risk

Medium-risk

Low-risk

0.4

0

Experiment Group

High-risk

Medium-risk

Low-risk

Date: 11/19/2020
PAWS Real-world Deployment
Cambodia: Srepok Wildlife Sanctuary
(ICDE 2020)

- 521 snares/month our tests
- 101 snares/month 2018
Previous Stage-by-Stage Method:
Make Prediction as Accurate as Possible Then Plan

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

Optimize

Maximize accuracy in Adversary target values *estimates*

Plan patrol Coverage
Game-Focused Learning: End-to-End Method Builds on Decision-focused Learning (AAAI 2019, AAAI 2020)

Maximize defender expected utility

\[ \sum (1 - p_i(\hat{q})) q_{\text{empirical}} \]

Plan patrol Coverage

Optimize

Maximize defender’s expected utility
Game-Focused Learning: Comparison to Two-Stage

![Graph showing comparison between Game-focused and Two-stage learning.](image)

- **Game-focused**
- **Two-stage**

**Expected utility** vs **Number of training games**

Date: 11/19/2020
PAWS Goes Global

Srepok, Cambodia
43,269 patrol observations
2013 – 2018

Royal Belum, Malaysia
824 patrol observations
June – August 2018
The Dual Mandate

**Data-rich parks:** build predictive models to plan patrols

**Data-scarce parks:** conduct patrols to detect illegal activity and improve the predictive model

[Gholami et al., AAMAS-18, Xu et al., ICDE-20]
**LIZARD: Multiarmed Bandit**
Lipschitz Arms with Reward Decomposability

**Theorem:** Given $N$ targets, Lipschitz constant $L$, and time horizon $T$, the regret bound of the LIZARD algorithm is $\text{Reg}(T) \leq O\left(\frac{4}{L^3} N T^{\frac{2}{3}} (\log T)^{\frac{1}{3}}\right)$:

- Input: $N$ Targets with features, $T$ Time Horizon
- Stochastic adversary, who places snares at targets
- Patrolling algorithm: Specify patrol effort in each target up to budget $B$
- Reduce regret wrt $OPT$, optimal patrol effort, for capturing snares

Lizard exploits decomposability, smoothness, monotonicity
Green Security Games: Integrating Real-Time “SPOT” Information (IAAI 2018)

Goal: automatically find poachers

Goal: automatically find poachers
Drone Used to Inform Rangers

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

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

- $\text{Prob}(\text{ranger arrives}) = 0.3$ [poacher may not be stopped]
- Deceptive signaling to indicate ranger is arriving
- Must be strategic in deceptive signaling
Exploiting Informational Advantage
Defender Knows Pure & Mixed Strategy
(AAAI 2018, AAAI 2020)

Si-G Model: Stackelberg Security Games with Optimal Deceptive Signaling

- Poacher best interest to “believe signal” even if know 50% defender deception
PAWS GOES GLOBAL with SMART platform!!

Protect Wildlife
800 National Parks
Around the Globe

Also: Protect Forests, Fisheries…
Future: AI for Social Impact (AI4SG or AI4SI)

Achieving social impact & AI innovation go hand in hand

Data to deployment: Not just improving algorithms, new AI4SI evaluation

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

Empower non-profits to use AI tools; avoid being gatekeepers to AI4SI tech
Key Collaborators on Papers Referenced
(In the order papers referenced)

- Eric Rice (USC)
- Nicole Immorlica (MSR)
- Yair Zick (UMASS, Amherst)
- Balaraman Ravindran (IIT-Madras)
- Amit Sharma (MSR)
- Maia Majumder (Harvard)
- Michael Mina (Harvard)
- Daniel Larremore (Colorado)
- Andy Plumptre (Cambridge)
- Rohit Singh (WWF)
- Phebe Vayanos (USC)
- Bistra Dilkina (USC)

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

@MilindTambe_AI
• The END
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:

\[
\frac{\partial \text{obj}(\text{decision})}{\partial \text{weights}} = \frac{\partial \text{prediction}}{\partial \text{weights}} \cdot \frac{\partial \text{decision}}{\partial \text{prediction}} \cdot \frac{\partial \text{obj}(\text{decision})}{\partial \text{decision}}
\]

Data Collection → Prediction \( g_i \) → Prescription \( \max_x \sum g_i(x_i) \) s.t. \( \sum x_i = 1 \) → Simulation \( f(x) \) → Field

Perrault, Wilder