AI and Multiagent Systems Research for Social Impact

Public Health

Conservation

Public Safety and Security
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: Social Networks, Game Theory
Reasoning with Social Networks

- Social networks to enhance intervention, e.g., HIV information
- Real-world pilot tests: Homeless youth shelters in Los Angeles
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…

Date: 12/14/2019
Public Safety and Security Optimizing Limited Intervention (Security) Resources

Stackelberg Security Games

- Game Theory for security resource optimization
- Real-world: US Coast Guard, US Federal Air Marshals Service…
Common Themes
Interdisciplinary Partnerships, Multiagent Systems, Data-to-deployment pipeline

Date: 12/14/2019
Common Themes
Interdisciplinary Partnerships, Multiagent Systems, Data-to-deployment pipeline

- Immersion
- Data Collection

- Predictive model
- Learning/Expert input

- Prescriptive algorithm
- Multiagent Reasoning; Intervention

- Field tests & deployment

Date: 12/14/2019
Fairness Challenges in AI for Public Health

Fairness challenges in intervention; not just prediction
Fairness Challenges in AI for Public Health

Fairness challenges in intervention; not just prediction

Data
- Partial Social network

Predict
- Link Prediction

Prescribe
- Select key influencers

Field tests
Fairness Challenges in AI for Public Health

Fairness challenges in intervention; not just prediction

Address fairness: Need collaboration of AI & public health stakeholders
Fairness & AI for Public Health

AI Interventions in Public health

- HIV prevention
- TB Prevention
- Suicide Prevention

Fairness challenges in intervention

PhD student photos in top right corner
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

**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

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<tr>
<th>Nature</th>
<th>Influencer’s oracle</th>
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Challenge: Multi-step Policy

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K = 4

1st time step

K = 4

2nd time step

Date: 12/14/2019
HEALER: POMDP Model for Multi-Step Policy
Robust, Dynamic Influence Maximization

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

Recruited youths:

<table>
<thead>
<tr>
<th>HEALER</th>
<th>HEALER++</th>
<th>DEGREE CENTRALITY</th>
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<td>62</td>
<td>56</td>
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12 peer leaders

Date: 12/14/2019
Results: Pilot Studies [2017]


Date: 12/14/2019
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: 12/14/2019
AI Assistant: HEALER
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
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: 12/14/2019
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: 12/14/2019
Improving TB interventions
Decision-Focused Methods (simulation study)

Decision focused learning improves TB interventions

Interventions: Decision-Focused Better

Date: 12/14/2019
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

▶ Suicide rate is significantly high among youth experiencing homelessness (~7%-26%)
Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks

- Worst case availability: constant-sum game against nature

**Algorithm**
Chooses K gatekeepers

**Nature**
Chooses some gatekeepers to not participate

\[ G = (N, E) \]
Fairness & AI for Public Health

AI and Public health

HIV prevention

TB Prevention

Suicide Prevention

Fairness challenges in intervention
Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks *(NeurIPS 2019)*

Is there any Inequality in coverage of marginalized populations?

<table>
<thead>
<tr>
<th>Network Name</th>
<th>Network Size</th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
<th>Mixed</th>
<th>Other</th>
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<tr>
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<td>70</td>
<td>36</td>
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Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks (NeurIPS 2019)

- Inequality in coverage of marginalized population

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Maximin Fairness: Towards addressing Fairness Challenges

- Maximin fairness constraints: Every group at least W coverage

\[
\max_{x \in \mathcal{X}} \min_{\xi \in \Xi} \max_{y \in \mathcal{Y}} \left\{ \sum_{n \in \mathcal{N}_c} y_n : y_n \leq \sum_{\nu \in \delta(n)} \xi_n \nu, \forall n \in \mathcal{N}_c \right\}
\]

\[
\mathcal{Y} := \left\{ y \in \{0, 1\}^N : \sum_{n \in \mathcal{N}_c} y_n \geq W|\mathcal{N}_c|, \forall c \in C, \forall \xi \in \Xi \right\}
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HIV Prevention in Marginalized Populations: Choose Peer Leaders *(IJCAI 2019)*

- Intervention: Influence maximization

- Are there any fairness violations?

![Fairness violation graph](image)

- Native American
- Asian
- Black
- Native Hawaiian
- White
- Latino

*Greedy*
HIV Prevention in Marginalized Populations: Choose Peer Leaders *(IJCAI 2019)*

- Are there any fairness violations?

Optimal value with $k = 3$: 4.25

**Constraint:** $f(S) \geq 4.25$

Optimal value with $k = 2$: 2.5

**Constraint:** $f(S) \geq 2.5$

Budget: $k = 5$
Multiobjective Influence Maximization
Towards Addressing Fairness Challenges

- Four networks from HIV prevention interventions: ~70 nodes each
- Compare standard greedy algorithm to both fairness concepts

Fairness violation

- Graph showing fairness violation for different groups:
  - Native American
  - Asian
  - Black
  - Native Hawaiian
  - White
  - Latino

Legend:
- Greedy
- FairInfluence
• Is more attention or less attention fair?

• What are fairness concerns in south Asian context?

• Is interpretability a requirement for fairness?
Fairness and AI for Public Health

Challenges in Intervention

*Fairness challenges in intervention; important to step beyond prediction*

*No consensus on exact fairness approach; rising concerns AI & fairness*

*Public health officials/stakeholders involved from start in fair solutions*

*Collaboration between AI systems & Stakeholders to address fairness*
Thank you!

Thank you

@MilindTambe_AI