



# AI for Social Impact: Results from deployments for public health and conservation



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**Google Research**

*Director “AI for Social Good”, Google Research India*



**@MilindTambe\_AI**

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# AI & Multiagent Systems Research for Social Impact

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**Public Health**



**Conservation**

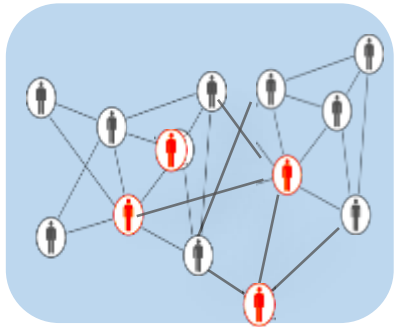


**Public Safety  
and Security**

**Optimize Our Limited Intervention Resources**

# Lesson #1: Achieving Social Impact and AI Innovation Go hand-in-hand

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**Social  
Networks &  
Bandits**

**Public Health**



**Green  
security  
games**



**Conservation**



**Public Safety  
& Security**



**Stackelberg  
security  
games**



## Lesson #2: Partnerships with Communities, NGOs & Govt organization crucial



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

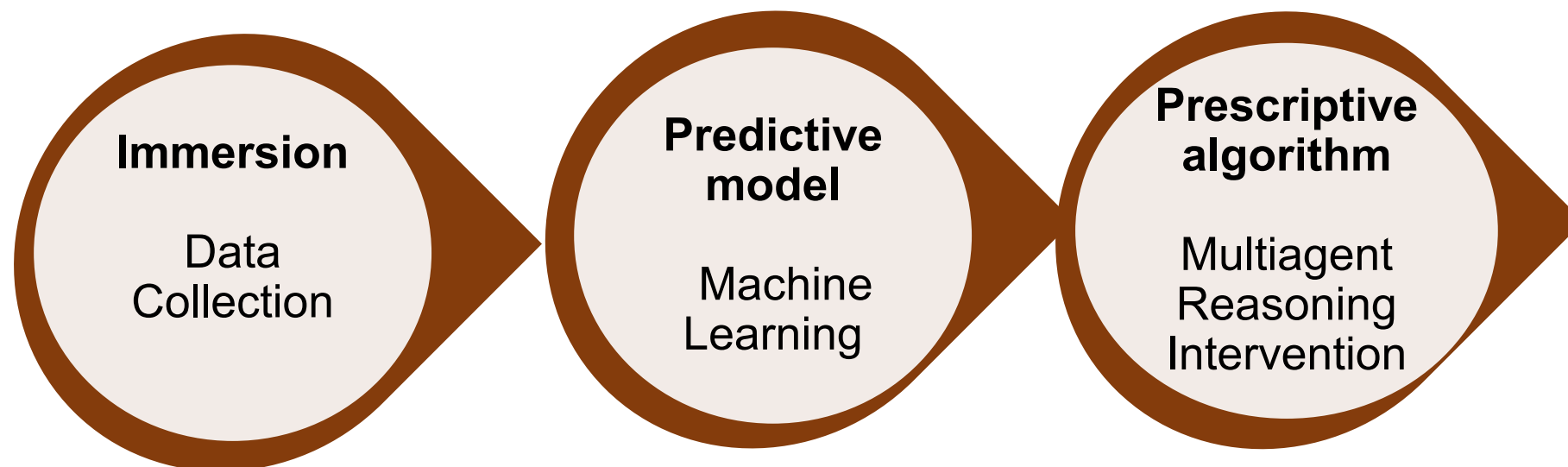




# Lesson #3:

## Data-to-deployment pipeline; not just improving algorithms

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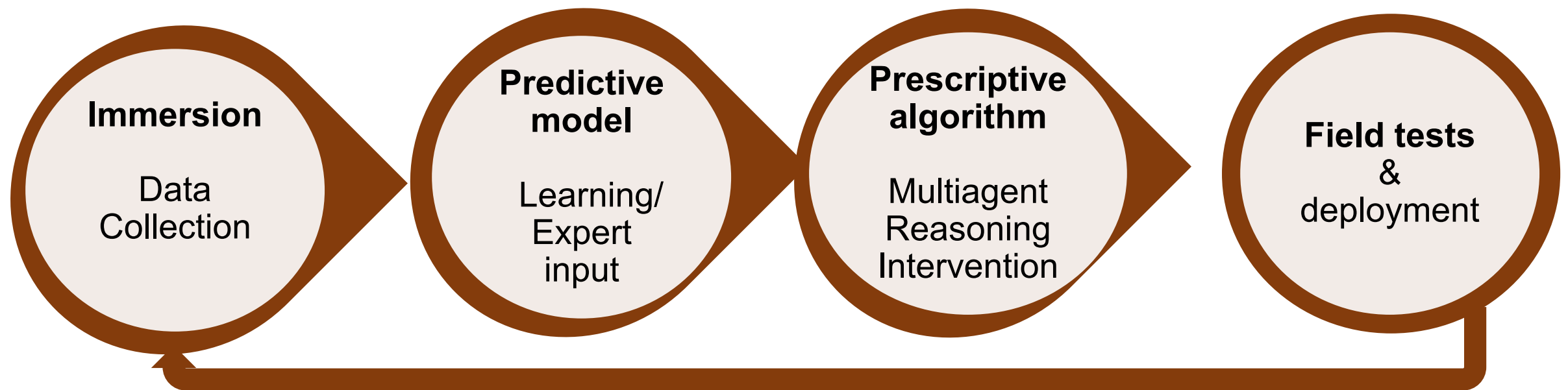


# Lesson #3:

## Data-to-deployment pipeline; not just improving algorithms

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Field test & deployment: Social impact is a key objective



# Outline

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## Public Health

- *Health information dissemination: Social networks*
- *Health program adherence: ML & Bandits*
- *COVID-19: Agent-based modeling*

## Conservation

- Cover papers from 2017-now [AAMAS, AAI, IJCAI, NeurIPS...]
- PhD students & postdocs highlighted



# Information dissemination & behavior change

## Optimizing Limited Intervention (Social Worker) Resources

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*Prevent HIV in youth experiencing homelessness: HIV 10x housed population*

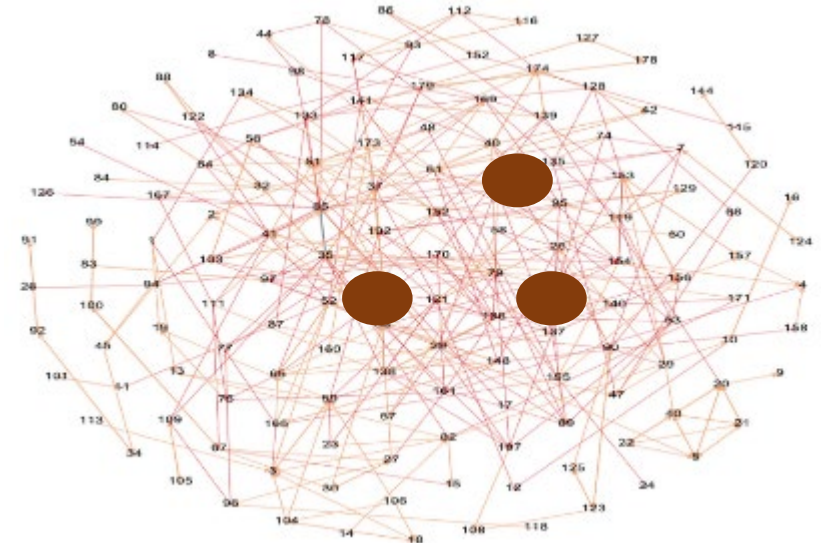
- **Shelters:** Limited number of peer leaders to spread HIV information in social networks
- “Real” face-to-face interactions; not Facebook etc



# Influence Maximization in Social Networks

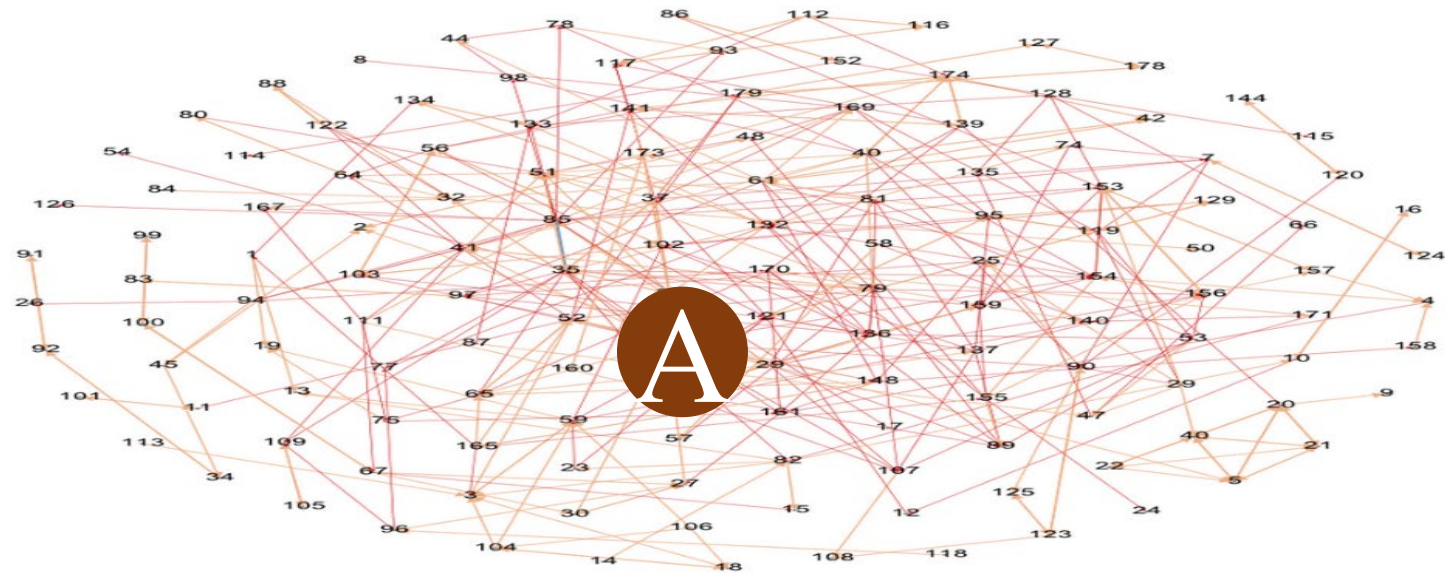
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- Given:
  - Social network Graph  $G$
  - Choose  $K$  “peer leader” nodes
  - Assume: Independent cascade model of information spread
- Objective:
  - Maximize expected number of influenced nodes

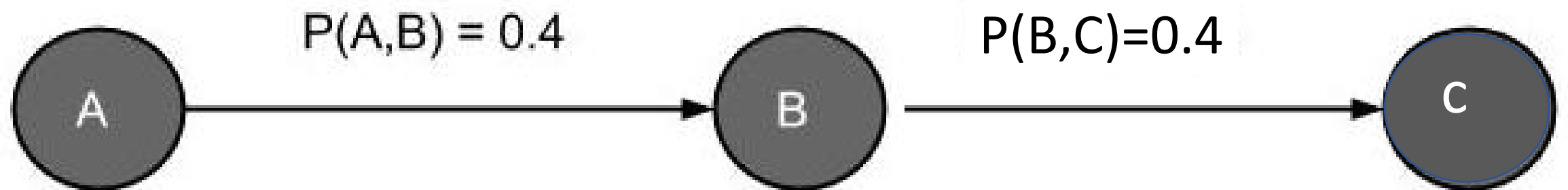


# Independent Cascade Model

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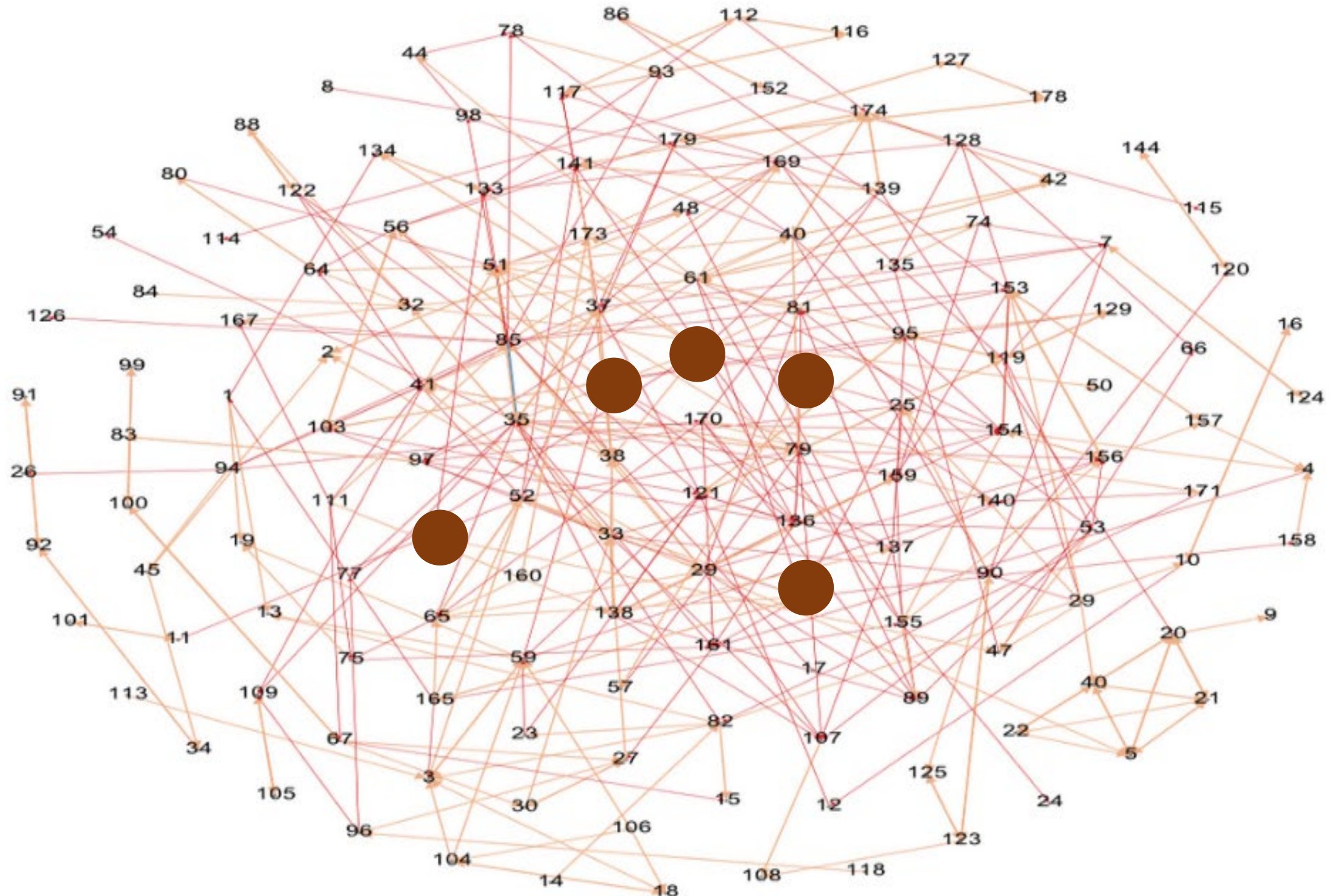
- Propagation Probability (for each edge)





# Influence Maximization (Budget = 5 nodes)

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## Lesson #4: Embrace interdisciplinary research

# Influence Maximization in Social Networks

## Three Key Challenges Combined Together

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*Research challenges in AI for social good?*

**Lesson #5:** *Lack of data & uncertainty is a feature (research challenge), not a bug*

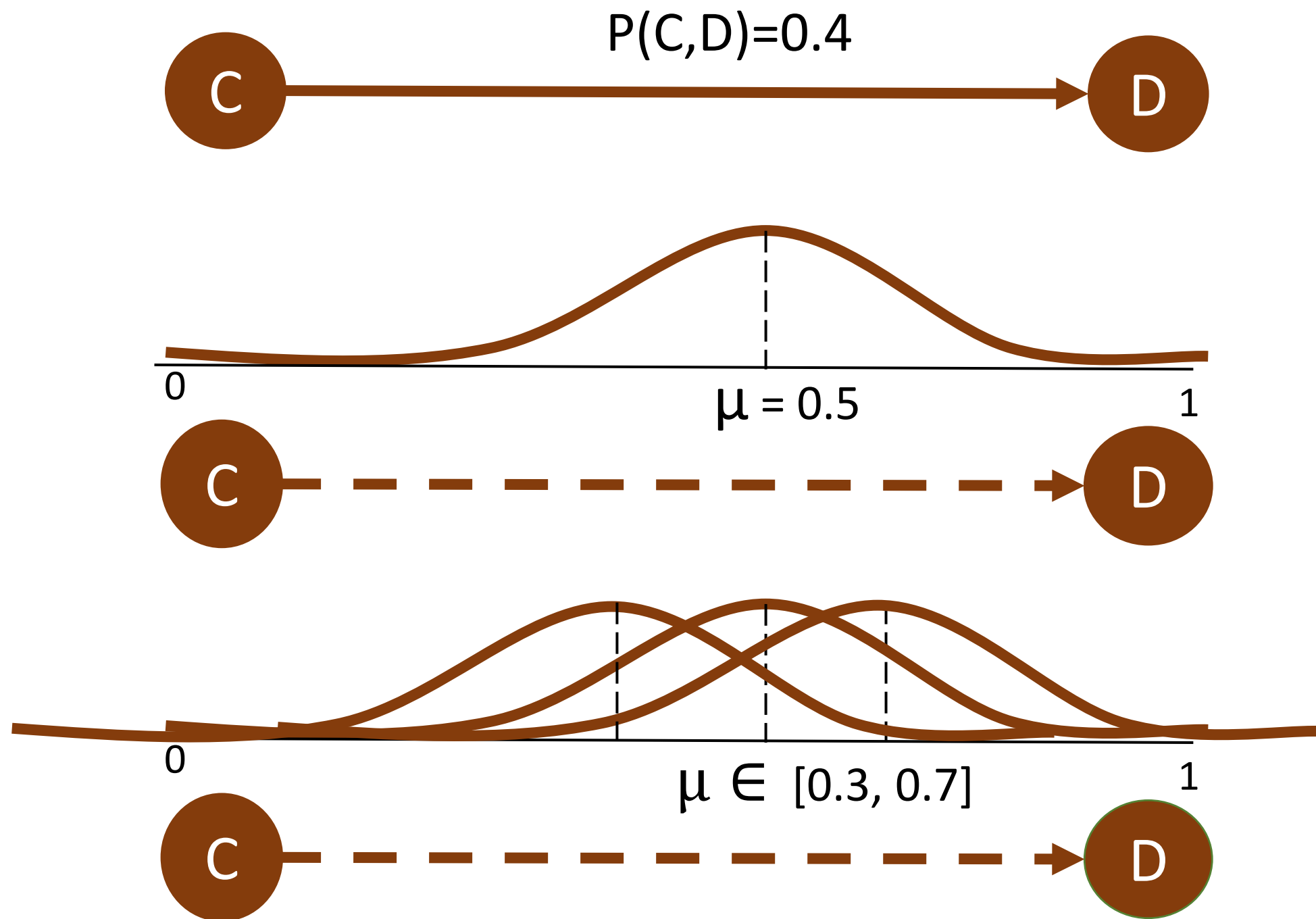
- Uncertainty in propagation probability over edges
- Unknown social network, limited query budget to uncover network
- Multi-step dynamic policies to handle peer leader “no shows”

*Sketch some ways we solve these problems*



# Challenge 1: Uncertainty in Real-world Physical Social Networks

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# Robust Influence Maximization

(AAMAS 2017)



Wilder

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

$$\max_{x \in \Delta^{|P|}} \min_{\mu, \sigma} \sum x_p \frac{(\text{Outcome}(p))}{OPT(\mu, \sigma)}$$

## Algorithm

Choose Peer Leaders  $p \in P$   
generating mixed strategy

“ $x \in \Delta^{|P|}$ ”

vs

## Nature

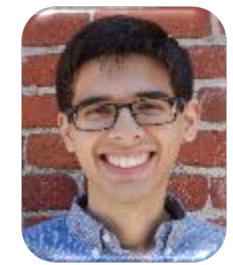
Chooses parameters

$\mu, \sigma$

# HEALER Algorithm

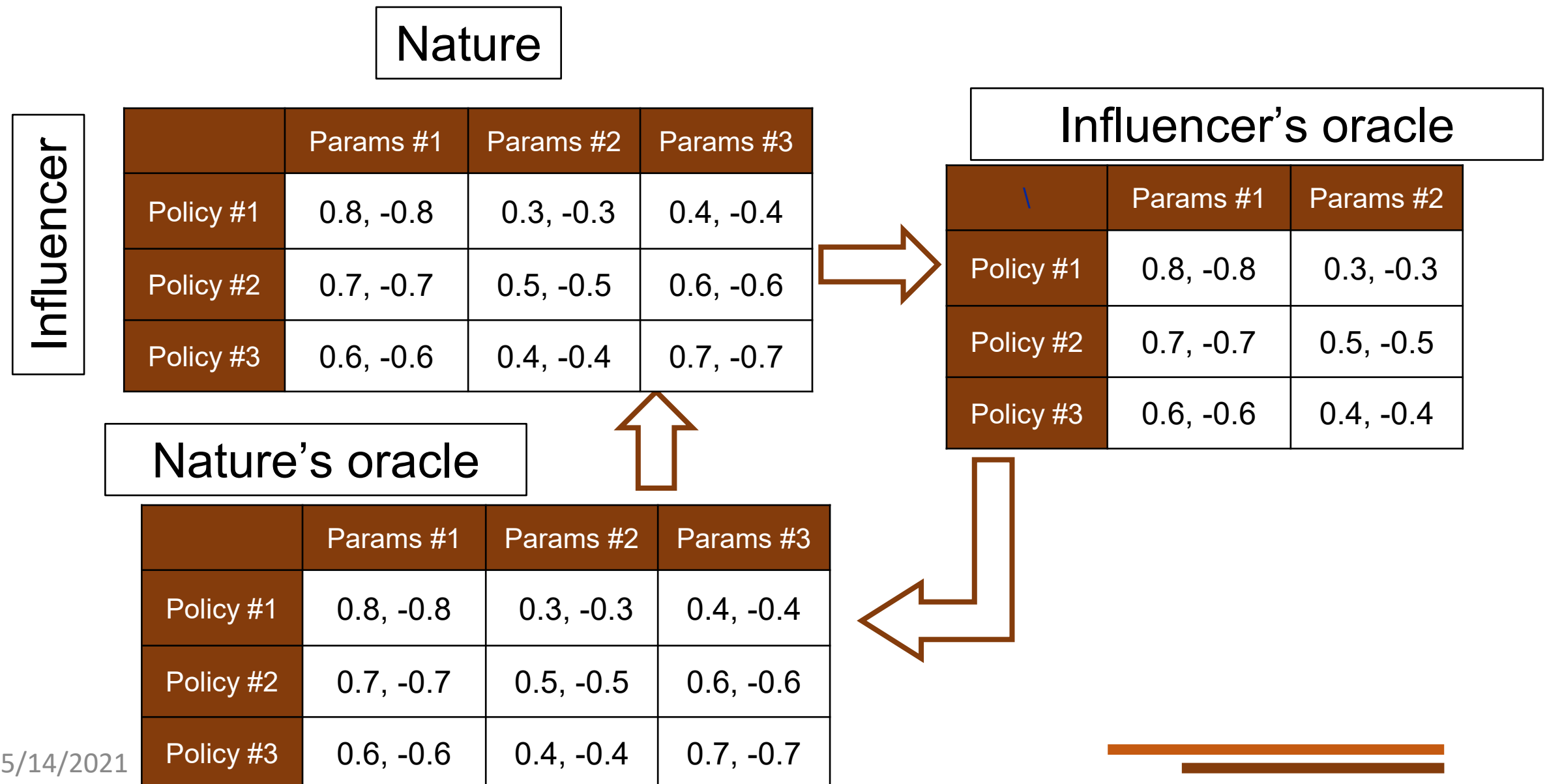
## Robust Influence Maximization

(AAMAS 2017)



Wilder

- Iterative algorithm: Double oracle





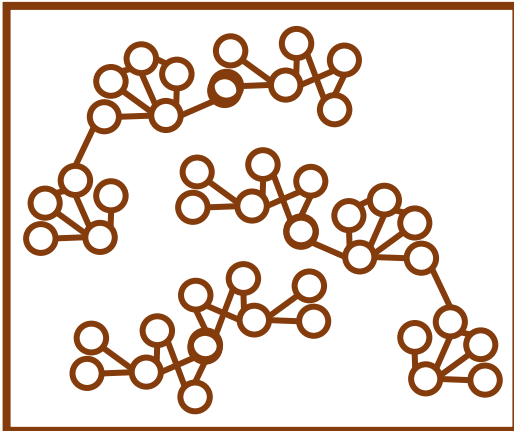
# Challenge 3: Sampling Networks: Exploratory Influence Maximization (AAAI 2018)

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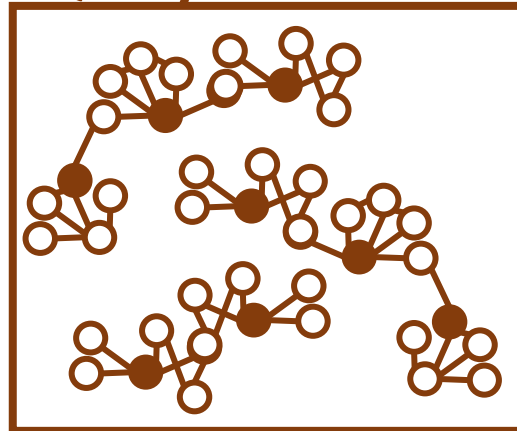


Wilder

Data collection costly



Query 15% nodes



Sampling Algorithm

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

- Query 15% of nodes in the population
- 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

Date: 5/14/2021

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# “Sampling-HEALER”

## Pilot tests with Homeless Youth

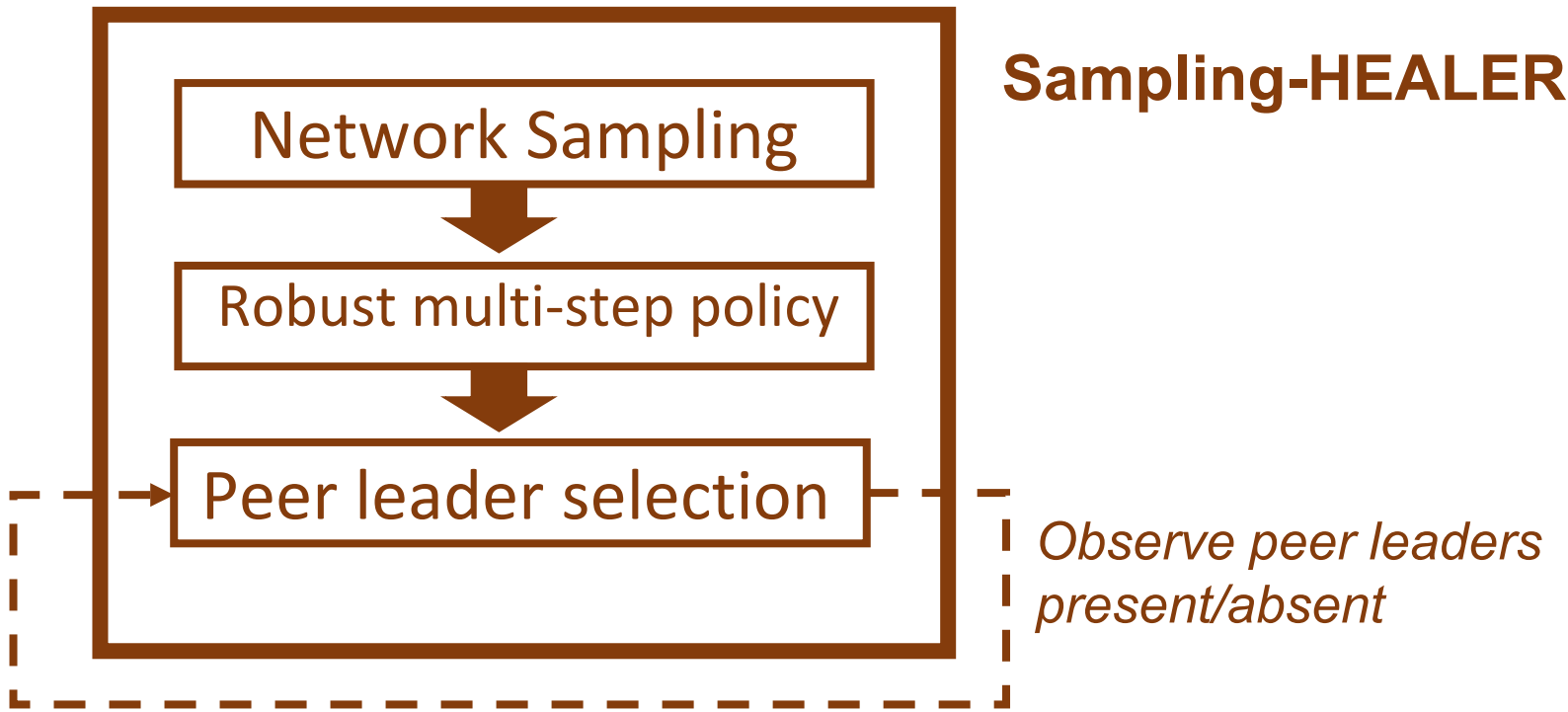
(IJCAI 2018)



Yadav



Wilder



12 peer leaders

Sampling HEALER (Sampled Network)	HEALER (Full Network)	DEGREE CENTRALITY (Full Network)
60 youth	62 youth	55 youth

# Results: Pilot Studies

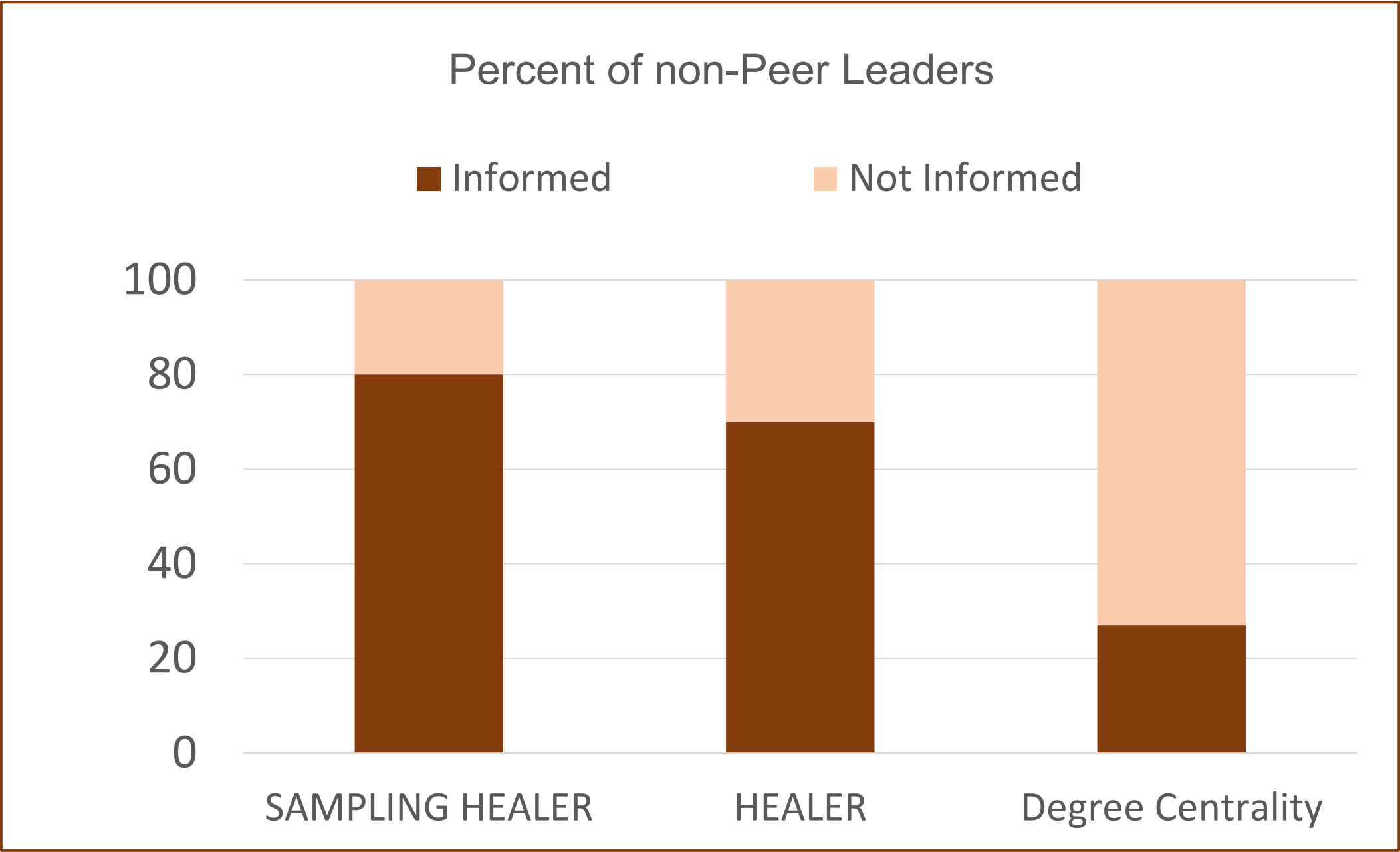
*(Journal of Society of Social Work & Research 2018)*



Yadav



Wilder



# Results of 750 Youth Study [with Prof. Eric Rice]

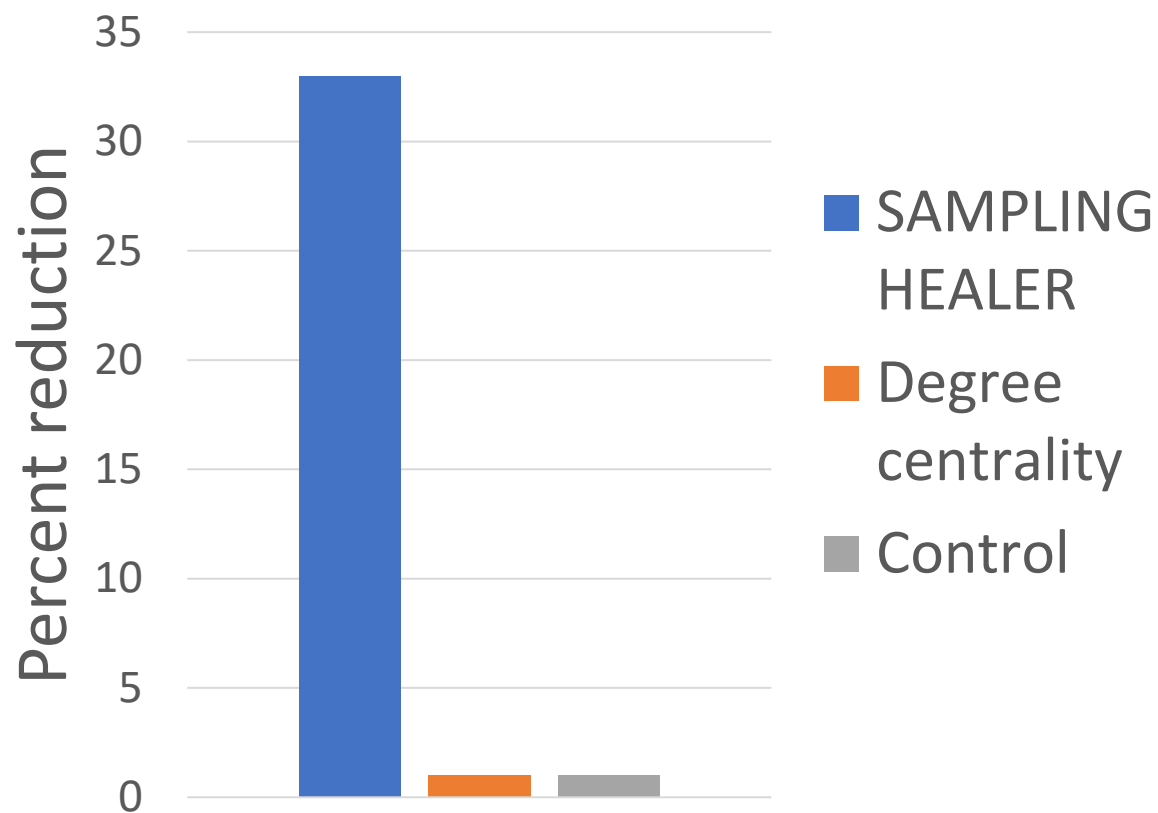
## Actual Change in Behavior?

(AAAI 2021)

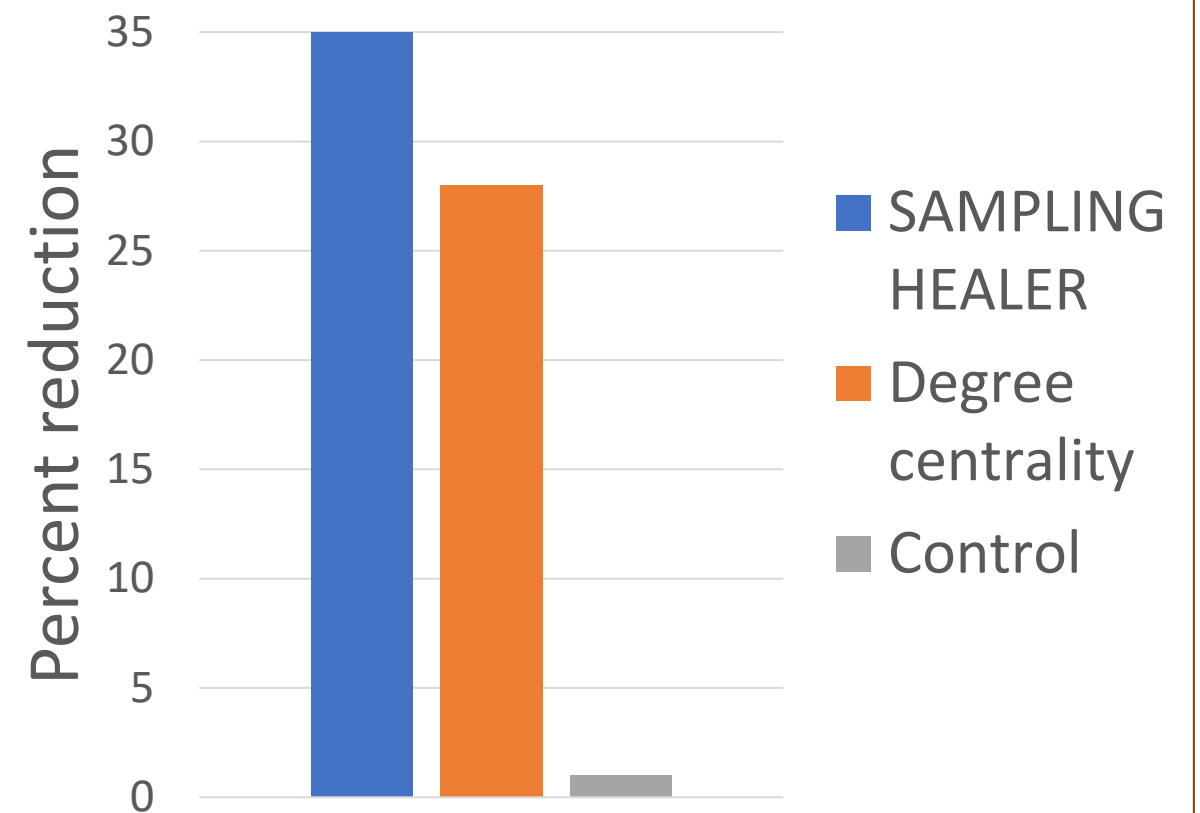
*First large-scale application of influence maximization for public health*



Reduction in condomless anal sex (1 month)



Reduction in condomless anal sex (3 months)

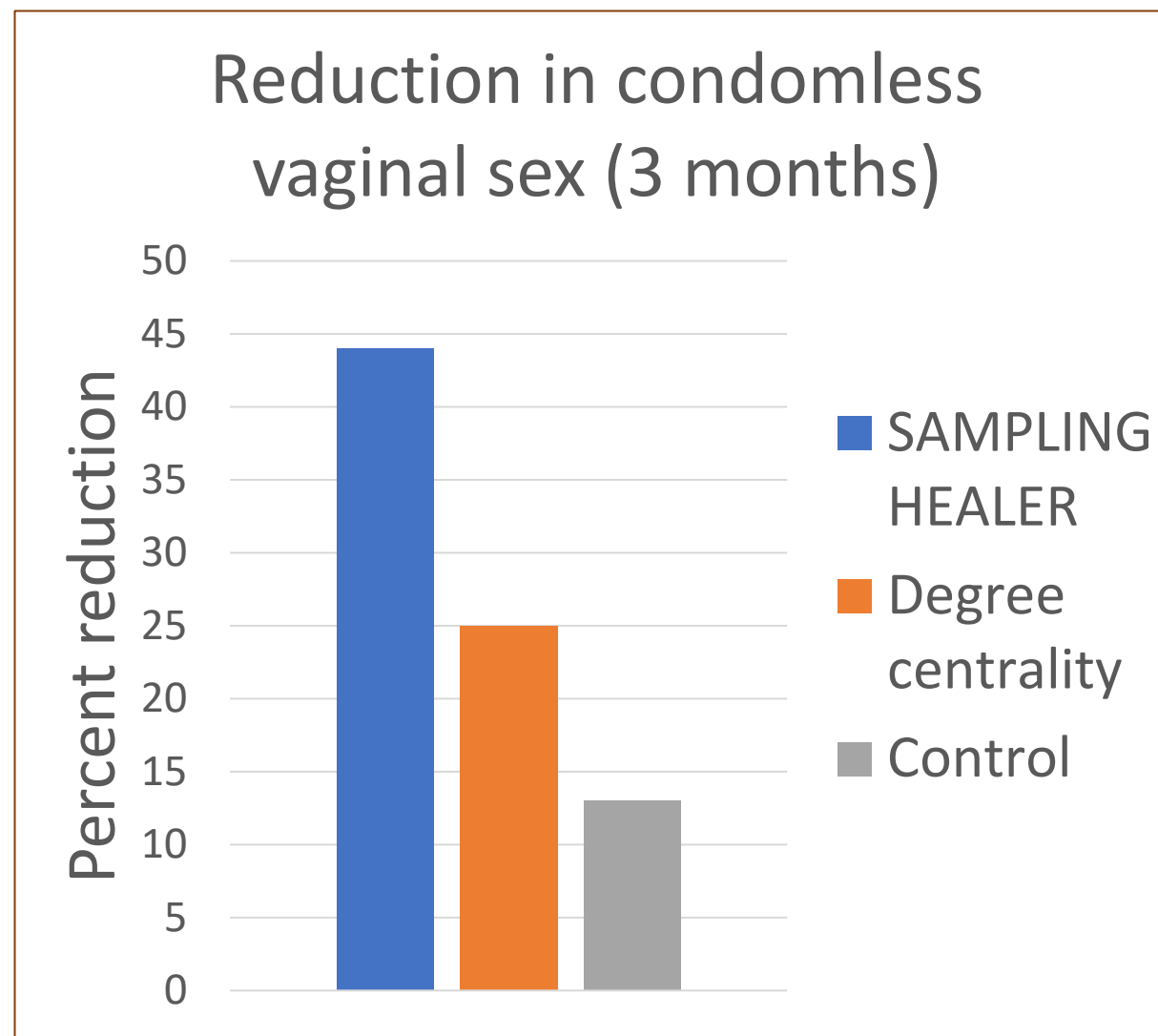


# Results of 750 Youth Study [with Prof. Eric Rice]

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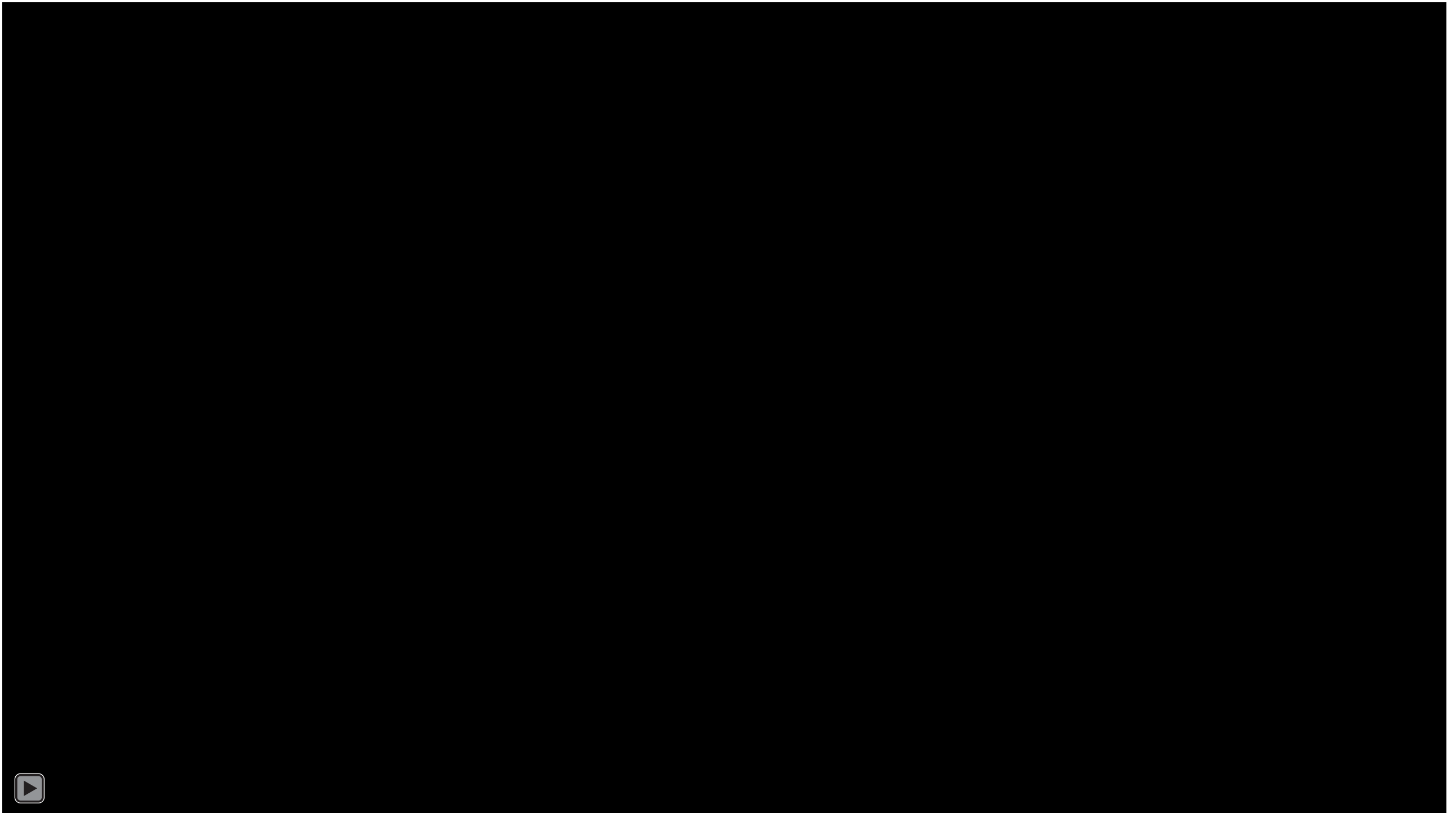
LOS  
ANGELES  
LGBT  
CENTER





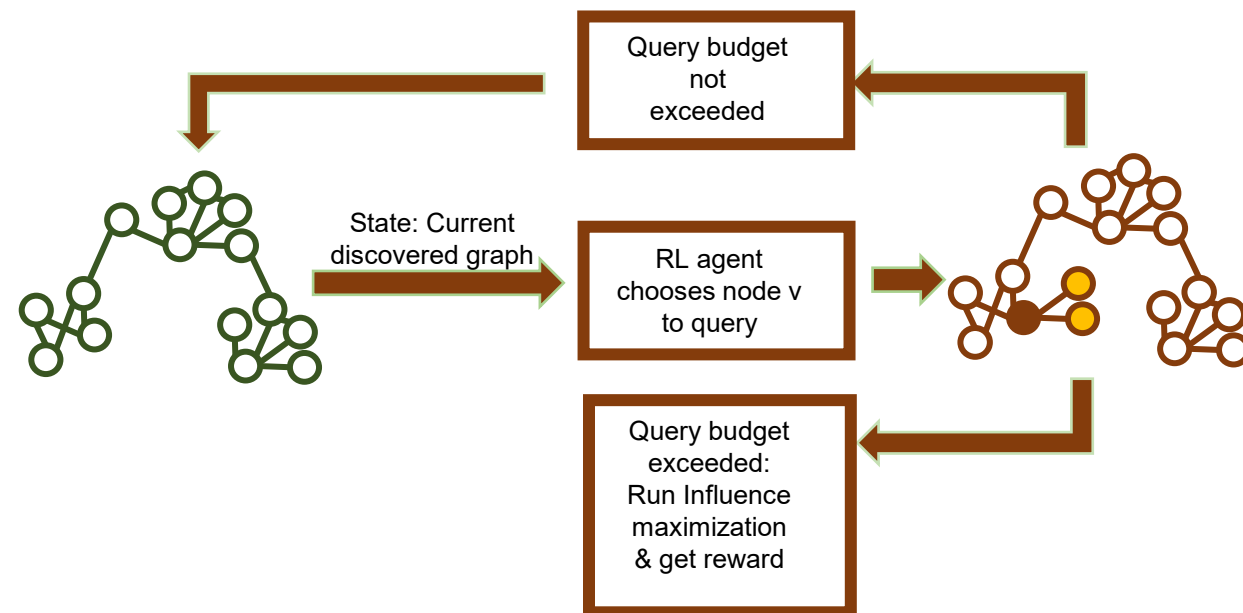
# What our collaborators are saying:

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# Next steps: RL for Influence Maximization in Social Networks

(with B. Ravindran & team, AAMAS 2020)

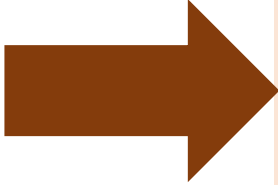


Network Family	Improve %
Rural	23.76
Animal	26.6
Retweet	19.7
Homeless	7.91

# Outline

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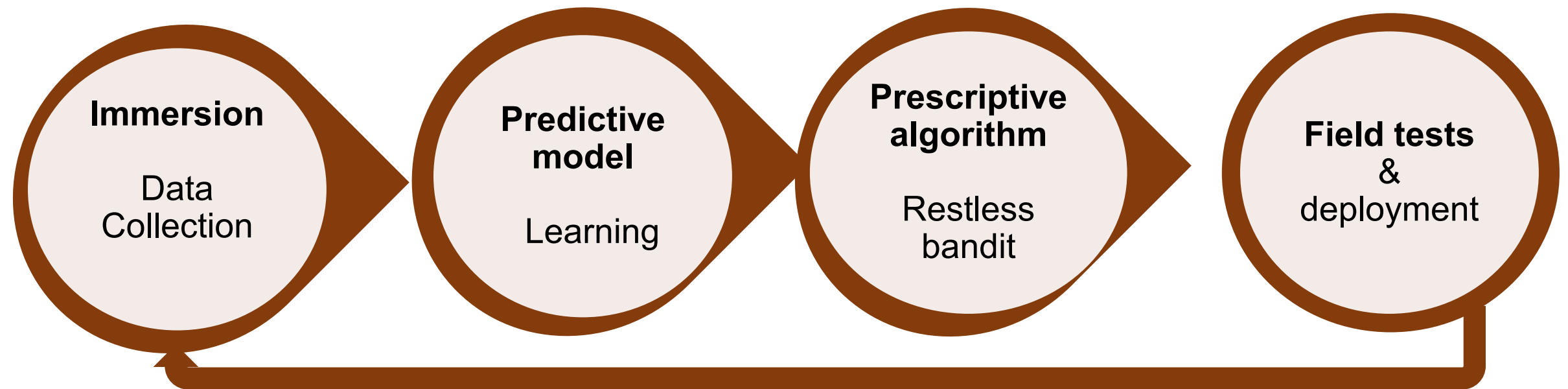
## Public Health

- 
- *Health information dissemination: Social networks*
  - *Health program adherence: ML & Bandits*
  - *COVID-19: Agent-based modeling*

## Conservation

# Intervention Reasoning: Active Adherence Monitoring

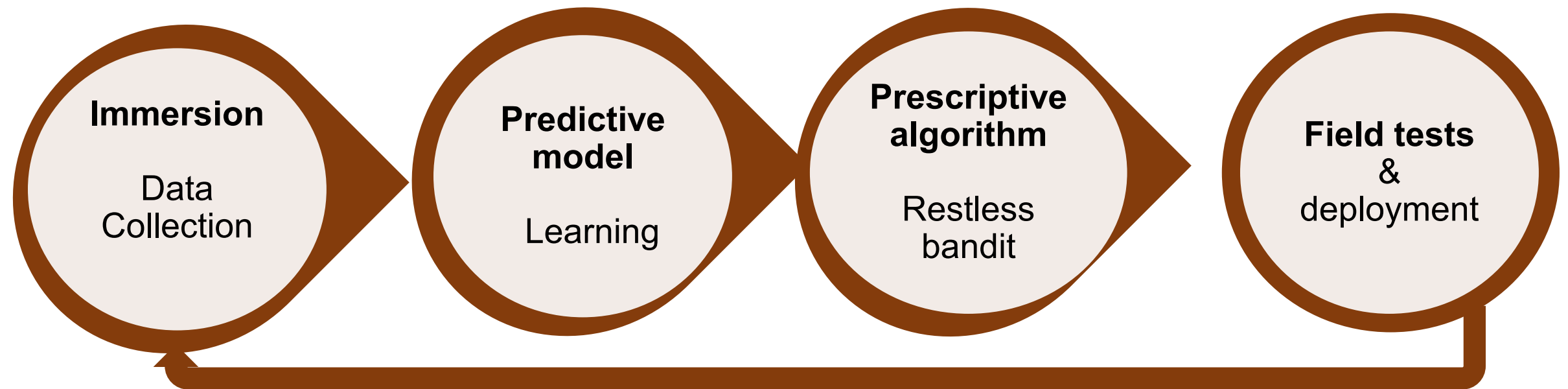
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# Intervention Reasoning: Active Adherence Monitoring

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# Health Program Adherence Maternal & Child Care in India

(IJCAI 2021)

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



*18 Million women*



*Weekly 3 minute call  
to new/expecting moms*



*mMitra: Significant benefits  
2.2 million women enrolled*

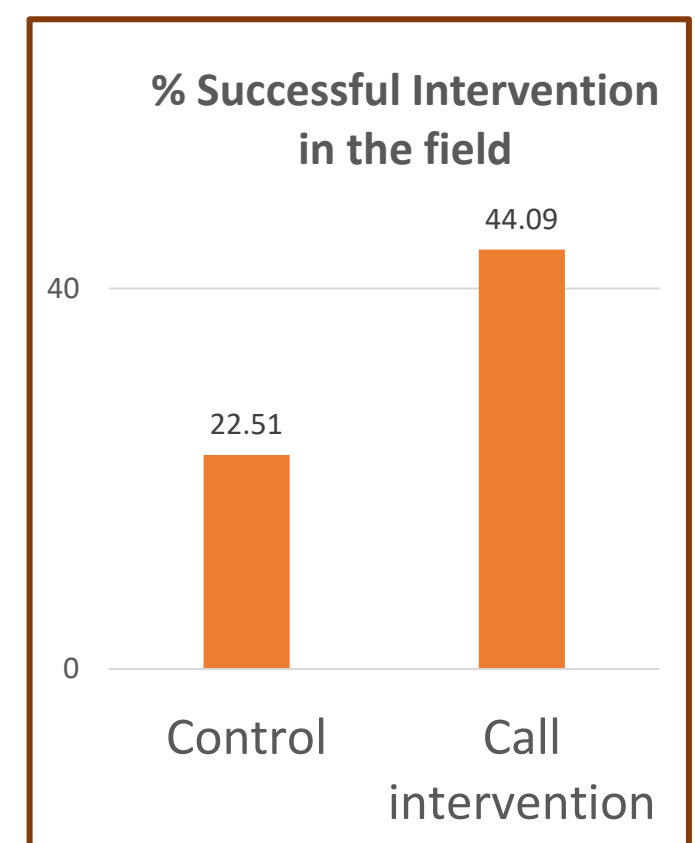
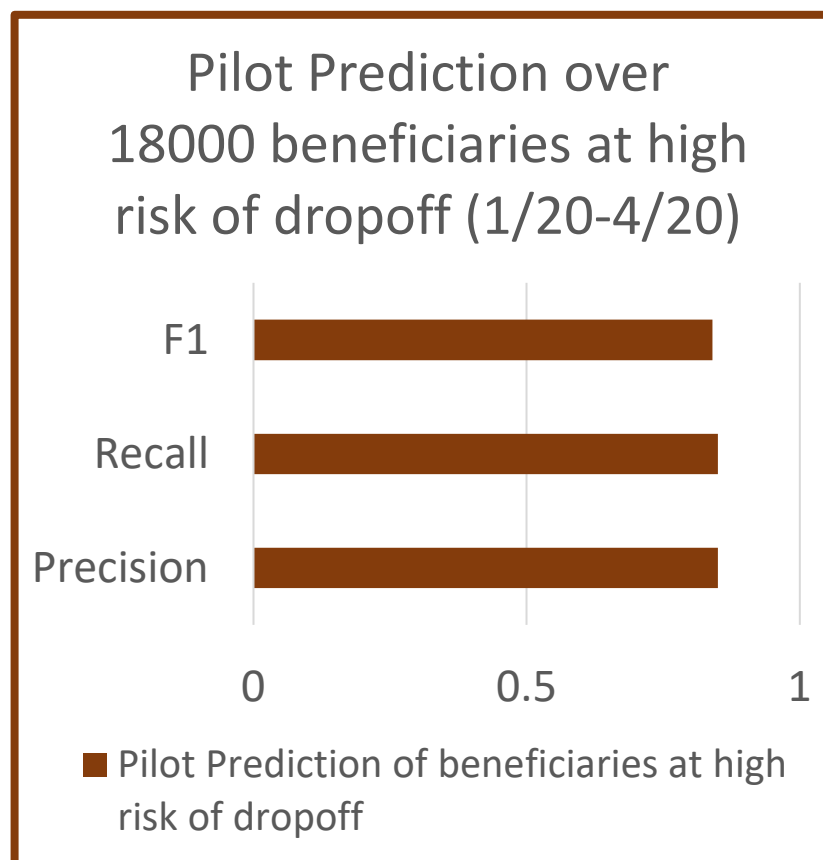
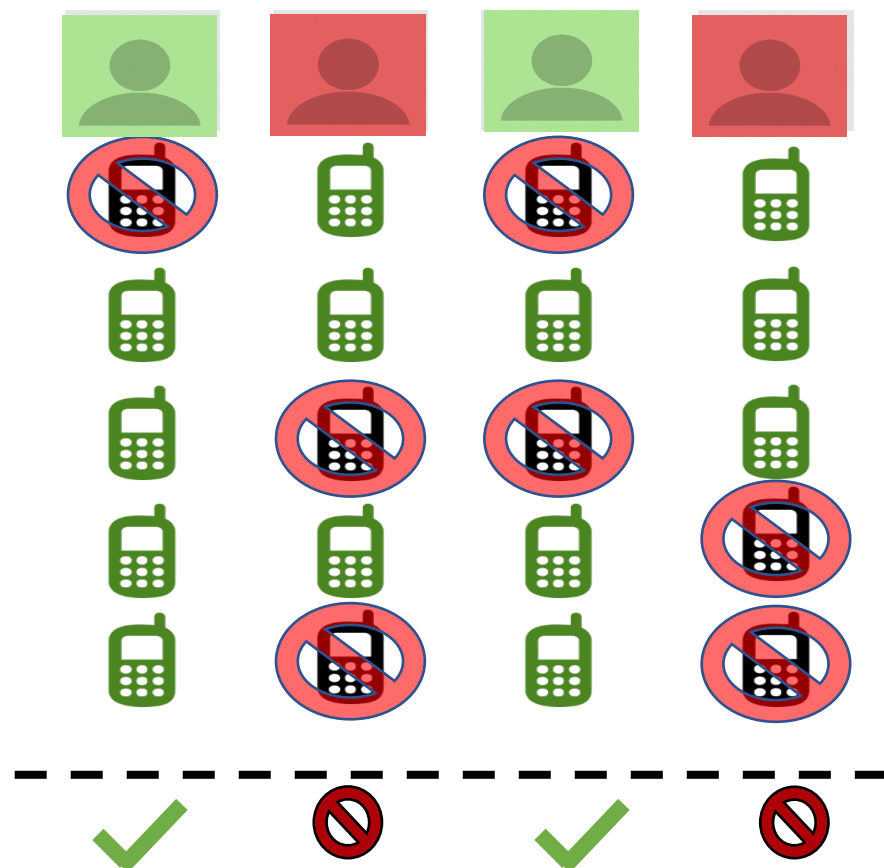
➤ *Unfortunately, significant fraction low-listeners or drop-outs*

# Passive Adherence Monitoring Maternal & Child Care in India

(with B Ravindran IIT Madras)

## **Classifier to predict beneficiaries drop out? So ARMMAN can focus interventions**

- Results of pilot with 18000 beneficiaries: High precision, recall, accuracy
- Field trial with 8000 beneficiaries: Call intervention helps
- **Prediction software in use to help 300,000 beneficiaries in mMitra**



# Passive Adherence Monitoring Preventing Tuberculosis in India

(KDD 2019)



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

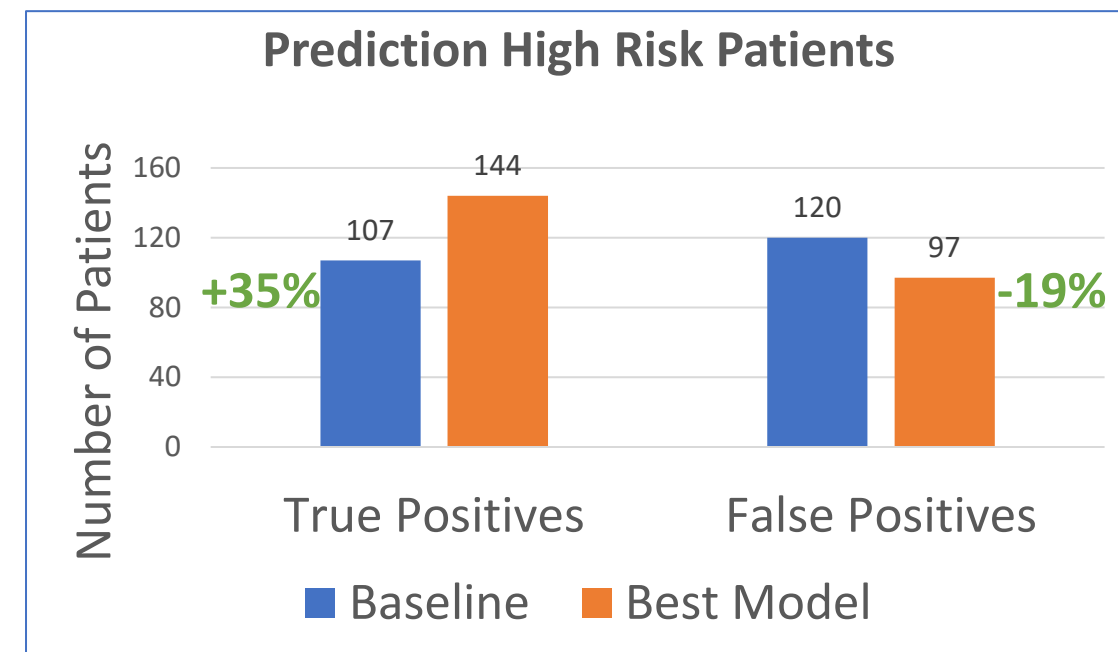
- *Predict adherence risk from phone call patterns for early intervention?*



*TB Treatment  
6 months of pills*



*Track adherence  
via daily phone calls*

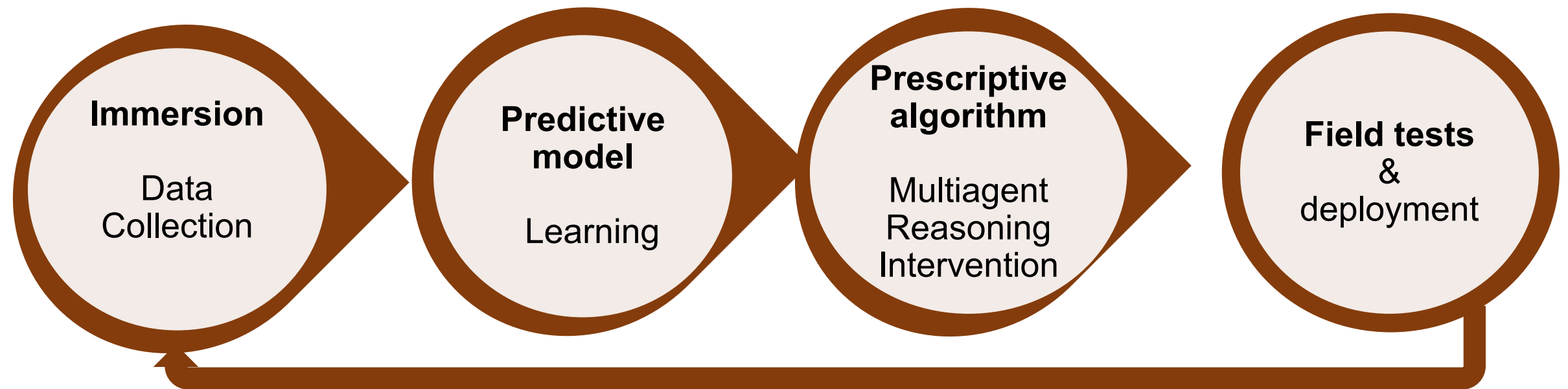


*Results Mumbai, India:* **everwell**  
*15,000 patients, 1.5 Million calls*



# Intervention Reasoning: Active Adherence Monitoring

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# Intervention Scheduling with Scarce Data: Active Adherence Monitoring

(NeurIPS 2020)



Mate



Killian

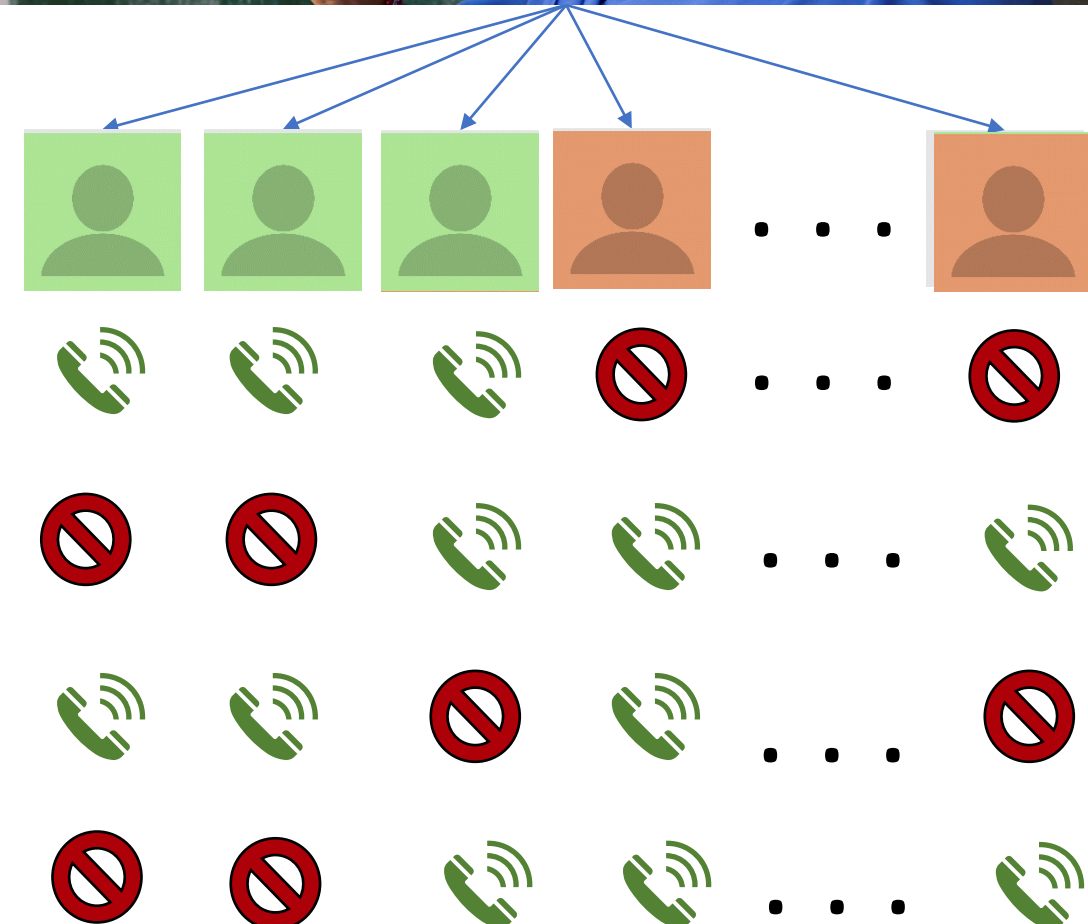
## Challenge:

- Large number of patients ( $N$ )
- Can only call  $K$  patients per day.
- Which  $K$ ?

## Approach: “Restless bandit”

- Each arm (patient) latent state  $\{0, 1\}$
- 0 = not-adhering; 1 = adhering

**Goal: Policy for  $K$  patients to call per day**



# New Fast Algorithm: Collapsing Bandits

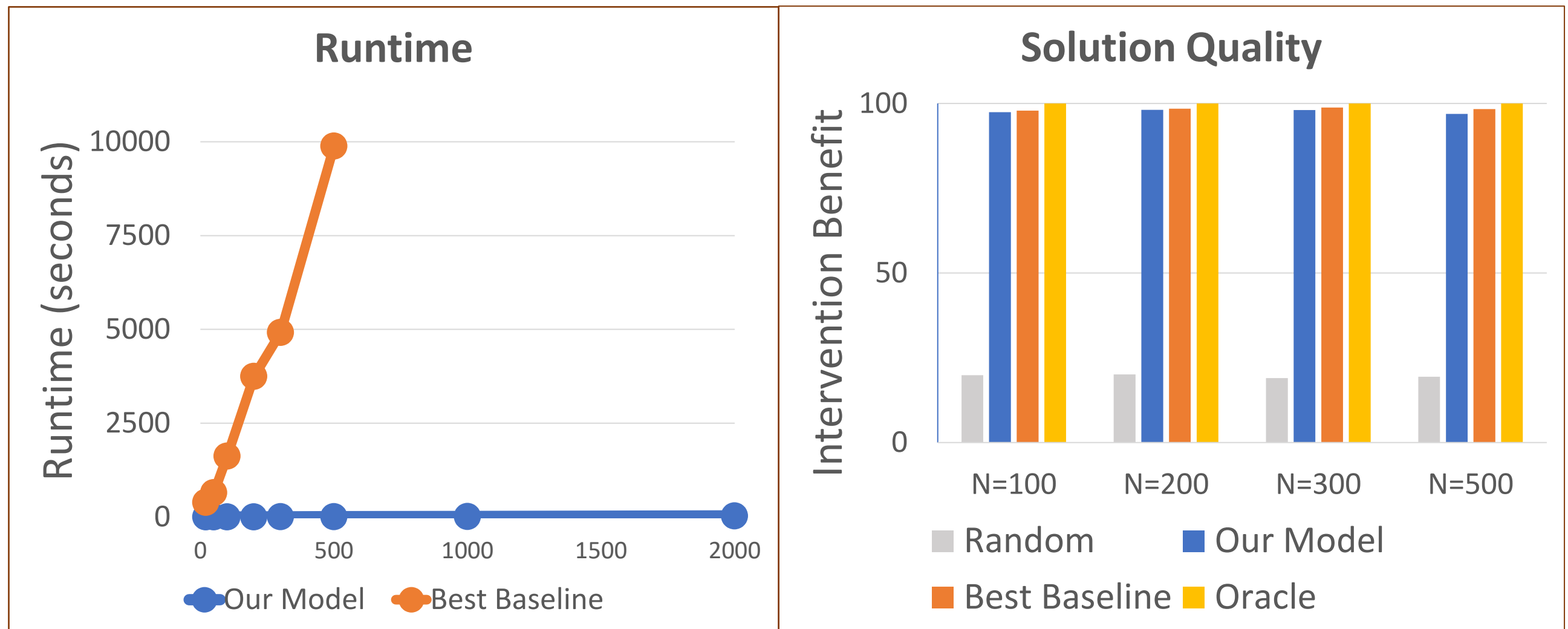


Mate



Killian

- *Orders of magnitude speedup with no solution quality loss*
- **ORANGE** = *Best baseline*
- **Blue** = *Our model*



# New Directions in Restless Bandits

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## *Restless bandits for intervention:*

➤ *20000 subject trial*





# Outline

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## Public Health

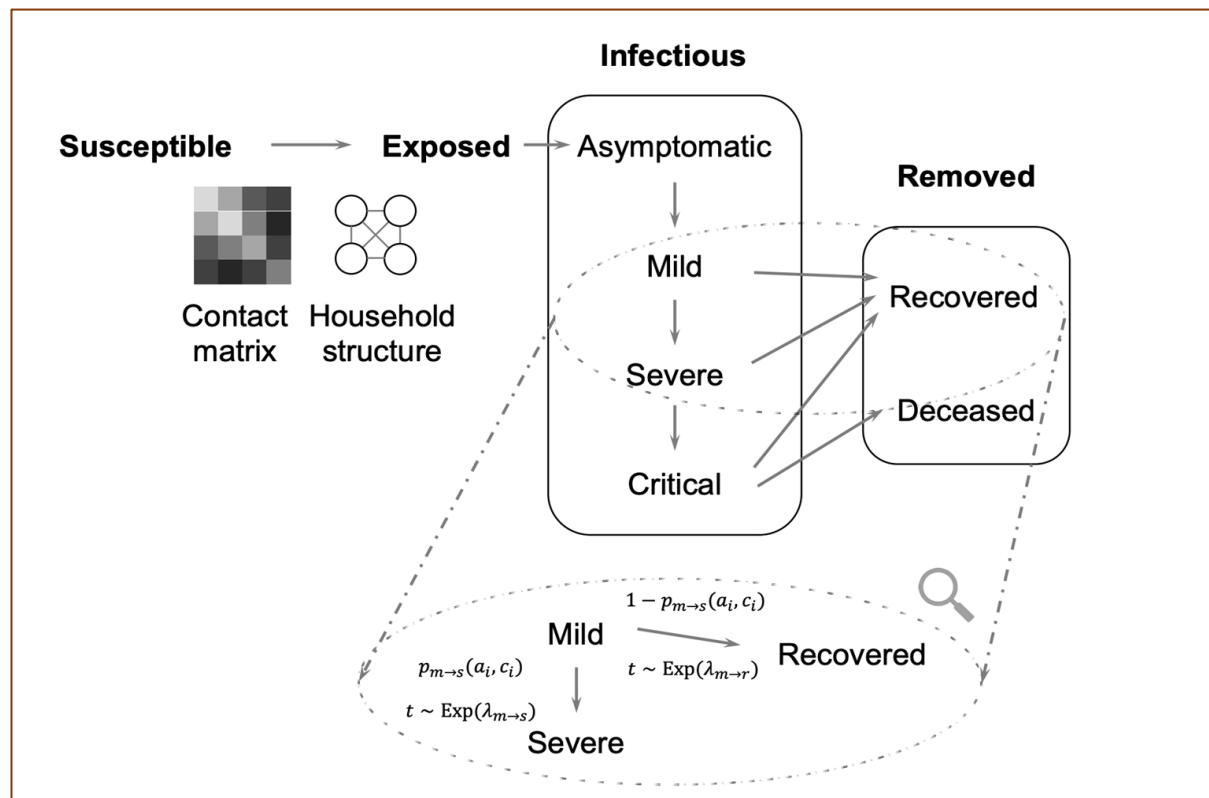
- *Health information dissemination: Social networks*
- *Health program adherence: ML & Bandits*
- *COVID-19: Agent-based modeling*

## Conservation

# COVID-19: Agent-based Simulation Model



Wilder

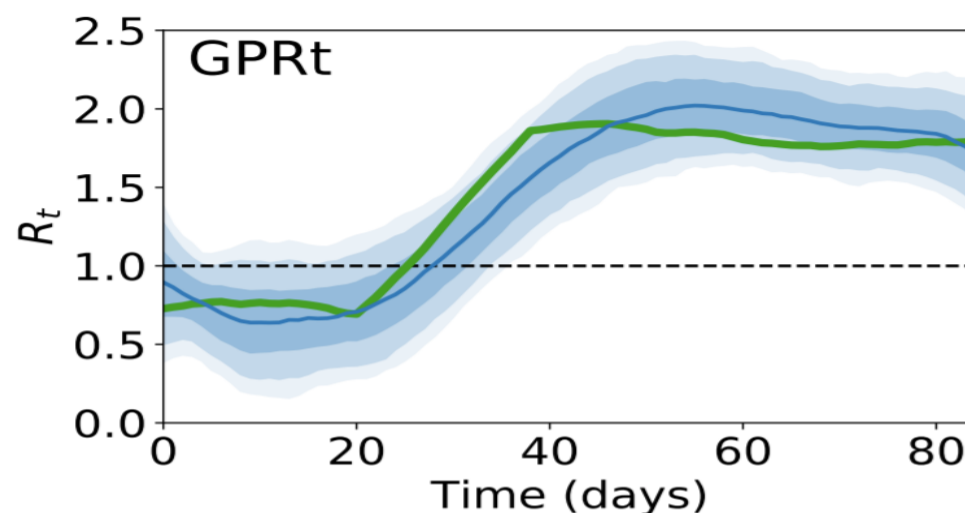


## RESEARCH ARTICLE

### Modeling between-population variation in COVID-19 dynamics in Hubei, Lombardy, and New York City

Bryan Wilder, Marie Charpignon, Jackson A. Killian, Han-Ching Ou, Aditya Mate, Shahin Jabbari, Andrew Perrault, Angel N. Desai, Milind Tambe, and Maimuna S. Majumder

PNAS October 13, 2020 117 (41) 25904-25910; first published September 24, 2020;  
<https://doi.org/10.1073/pnas.2010651117>



### Tracking disease outbreaks from sparse data with Bayesian inference

Bryan Wilder,<sup>1</sup> Michael Mina<sup>2</sup>, Milind Tambe<sup>1</sup>

<sup>1</sup> John A. Paulson School of Engineering and Applied Sciences, Harvard University

<sup>2</sup> T.H. Chan School of Public Health, Harvard University

[bwilder@g.harvard.edu](mailto:bwilder@g.harvard.edu), [mmina@hsph.harvard.edu](mailto:mmina@hsph.harvard.edu), [milind\\_tambe@harvard.edu](mailto:milind_tambe@harvard.edu)

# COVID Testing Policy: Accuracy vs Ease

(*Science Advances*, 2020) with *Prof. Michael Mina*



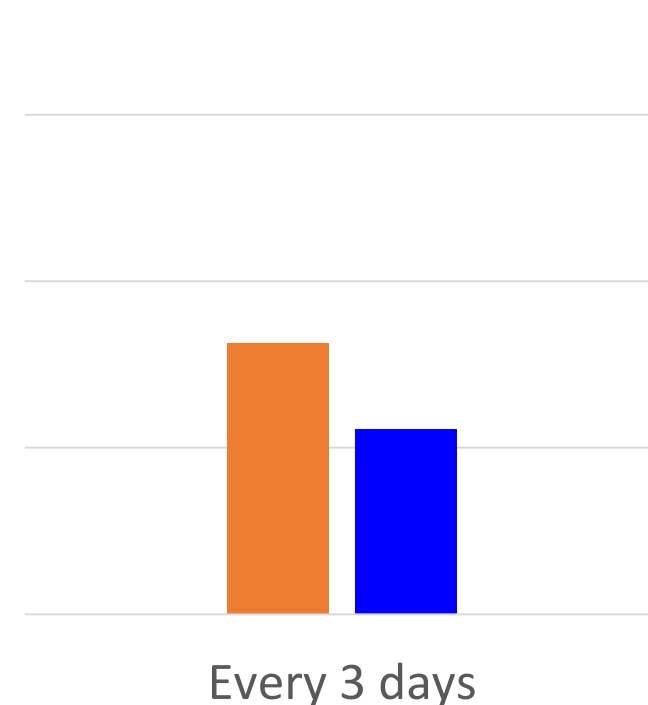
Wilder

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

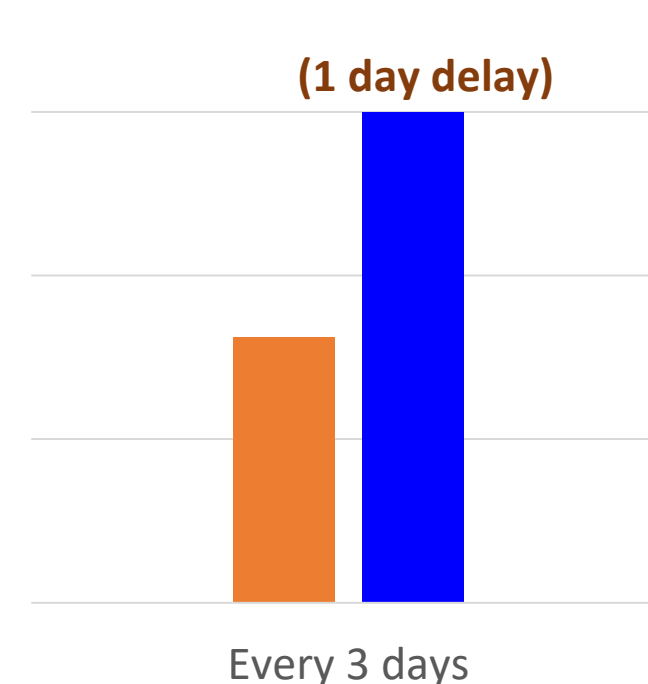
**Rapid turnaround time & frequency more critical than sensitivity for COVID-19 surveillance**

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

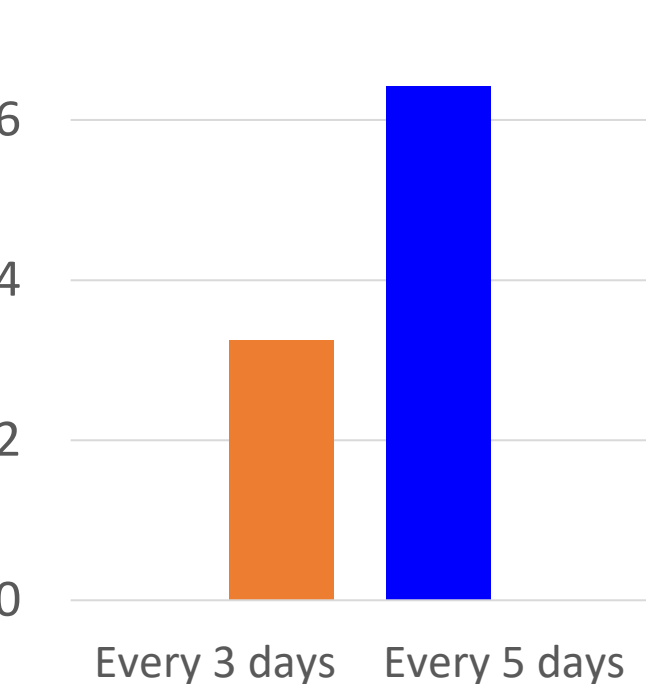
Total infections



Total infections



Total infections



# COVID Testing Policy: Impact

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





# COVID Testing Policy: Impact

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The Abbott BinaxNOW COVID-19 at-home test was one of two to receive FDA approval this week. The over-the-counter test does not need a prescription.

Courtesy of Abbott

HEALTH & MEDICINE

## Approval of at-home tests releases a powerful pandemic-fighting weapon



Chan School's Mina says despite vaccination campaign success, diagnostic tools still important

One of them is Michael Mina, assistant professor of epidemiology, who has called on federal regulators for much of the past year to clear the rapid antigen tests, arguing that widespread, frequent use of the diagnostic has the potential to stop outbreaks early and keep case numbers down.



# Outline

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Public Health



Conservation

- *Protect wildlife, forests, fisheries: Game-focused learning*
- *Integrating real time data for protection: Signaling games*

# Protecting Conservation Areas: Green Security Games

(IJCAI 2015)



Fang



Snare or Trap



Wire snares



Lesson: Step out of  
the lab & into the field



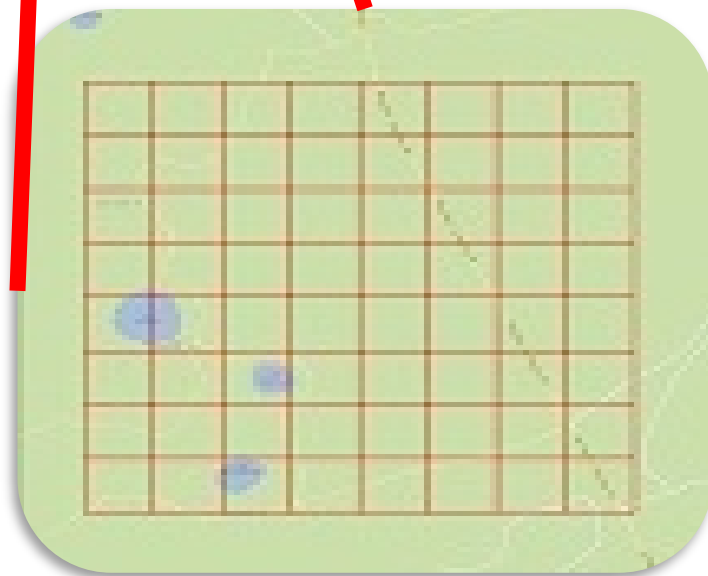
# From Stackelberg Security Games to Green Security Games

(IJCAI 2015)

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- *Learn poacher response model at each target*
- *So can figure out response by patrols*



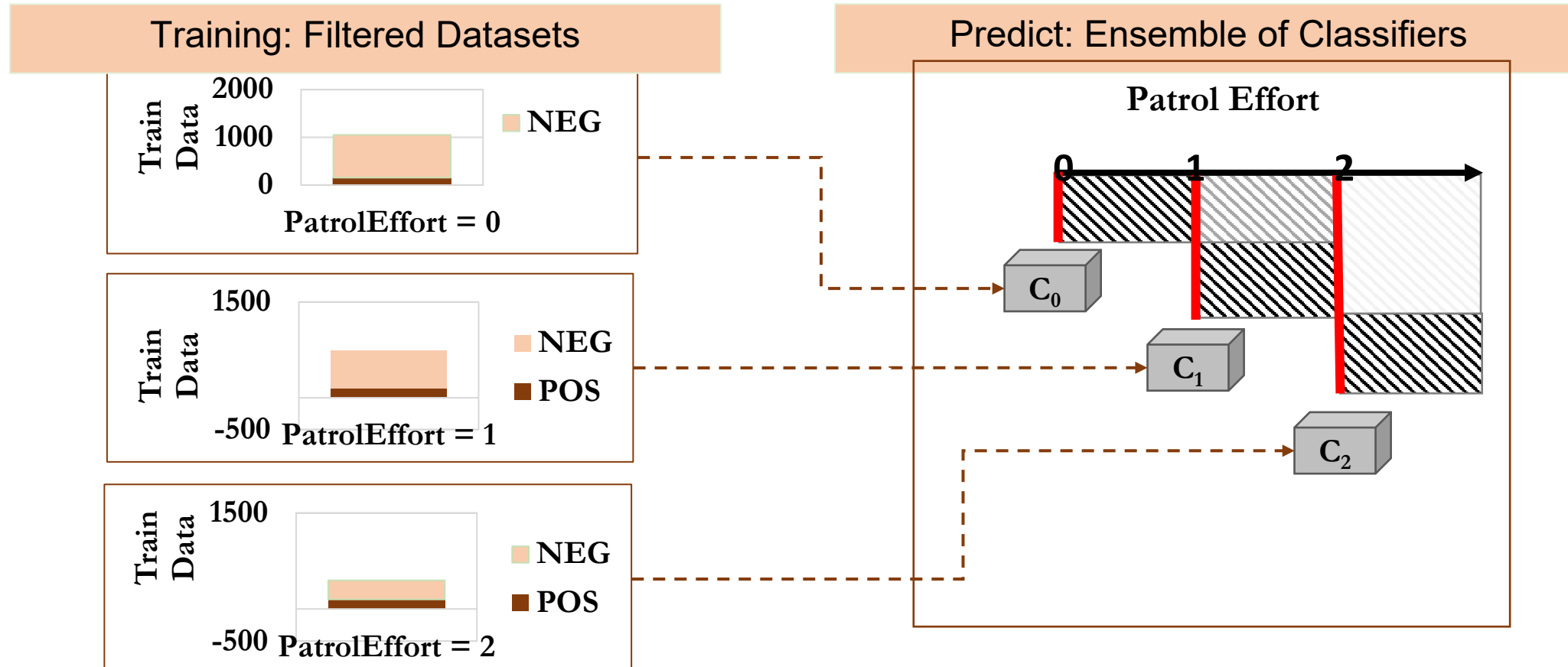
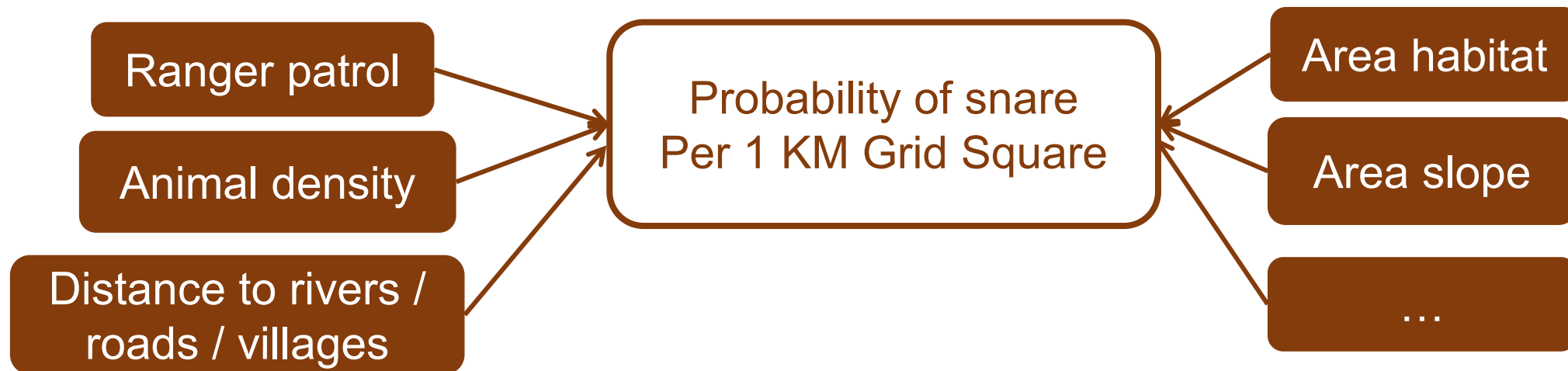
# Learning Adversary Response Model: Uncertainty in Observations



Nguyen



Gholami





# PAWS: First Pilot in the Field

(AAMAS 2017)



Ford

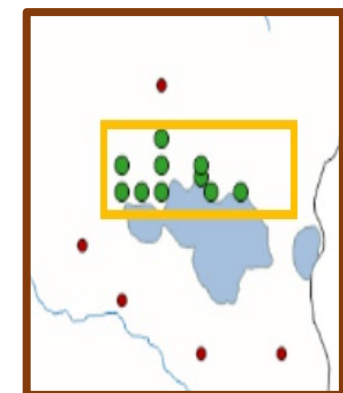
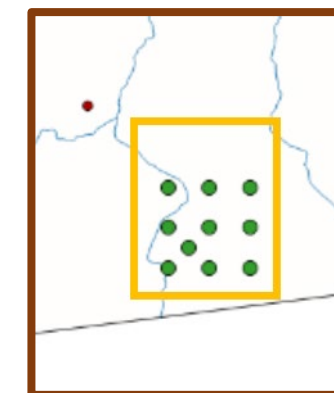
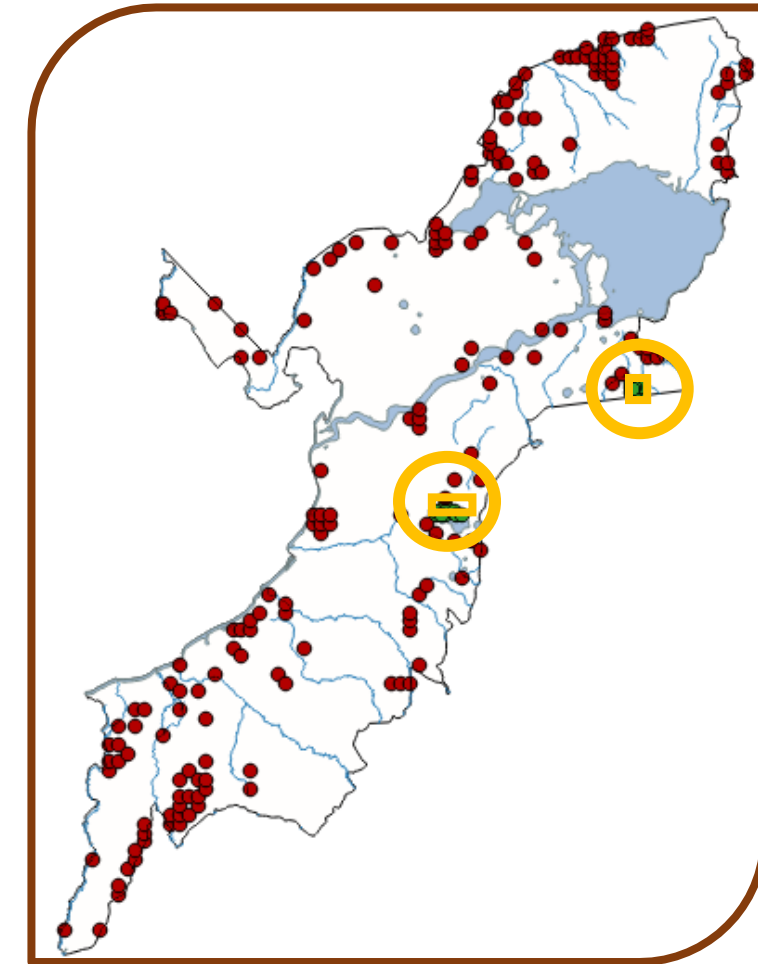


Gholami

- 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

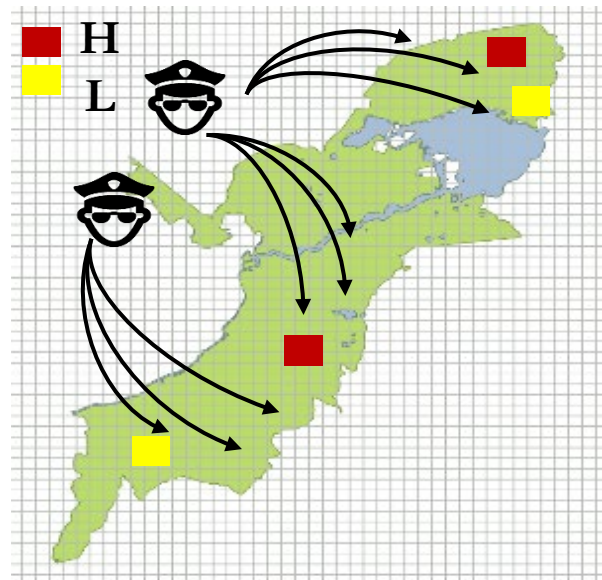
(ECML PKDD 2017, ICDE 2020)



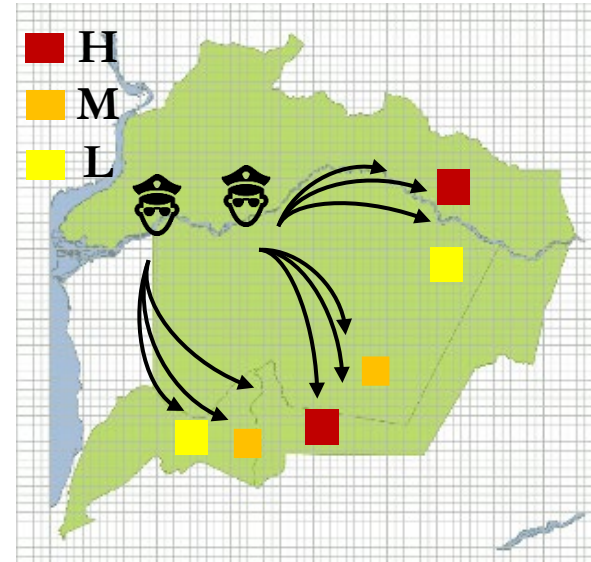
Xu



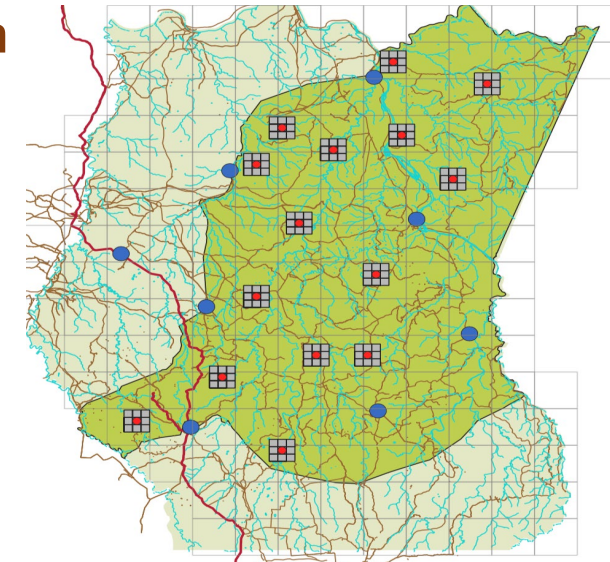
Gholami



Queen Elizabeth National Park

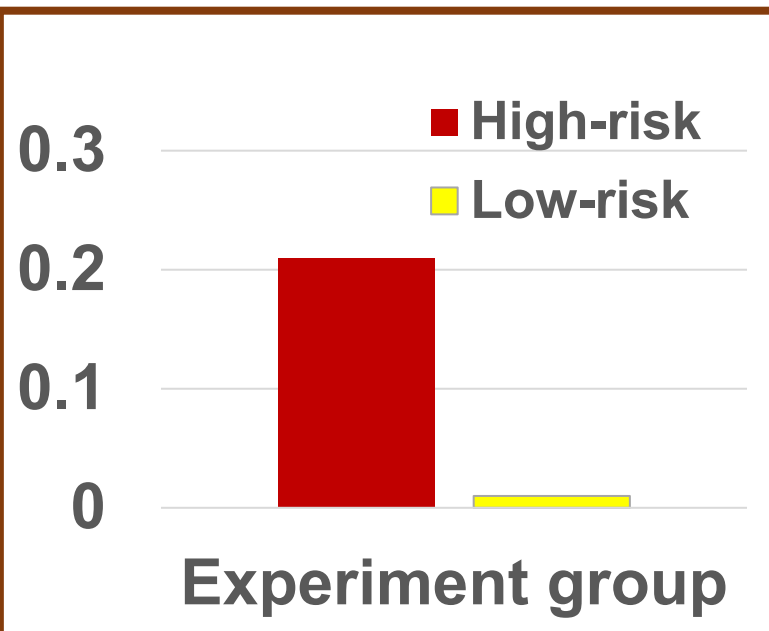


Murchison Falls National Park

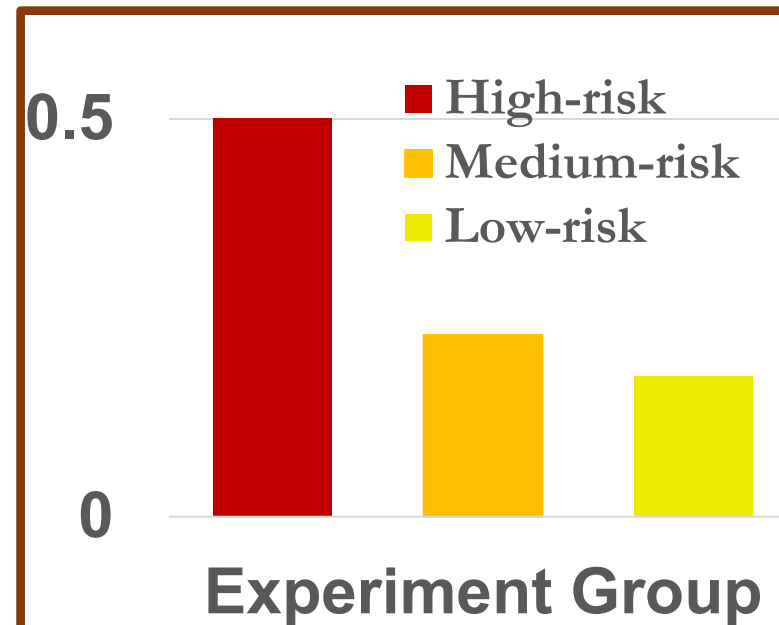


Srepok Wildlife Sanctuary

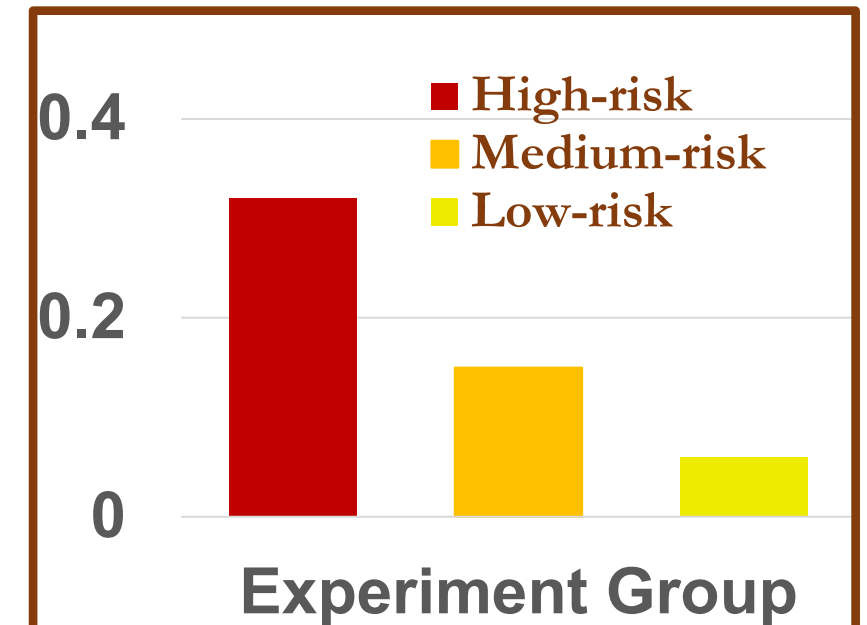
Snares per patrolled sq. KM



Snares per patrolled sq. KM



Snares per patrolled sq. KM





# PAWS Real-world Deployment Cambodia: Srepok Wildlife Sanctuary

(ICDE 2020)



Xu



**2019 PAWS:** *521 snares/month*

VS

**2018:** *101 snares/month*

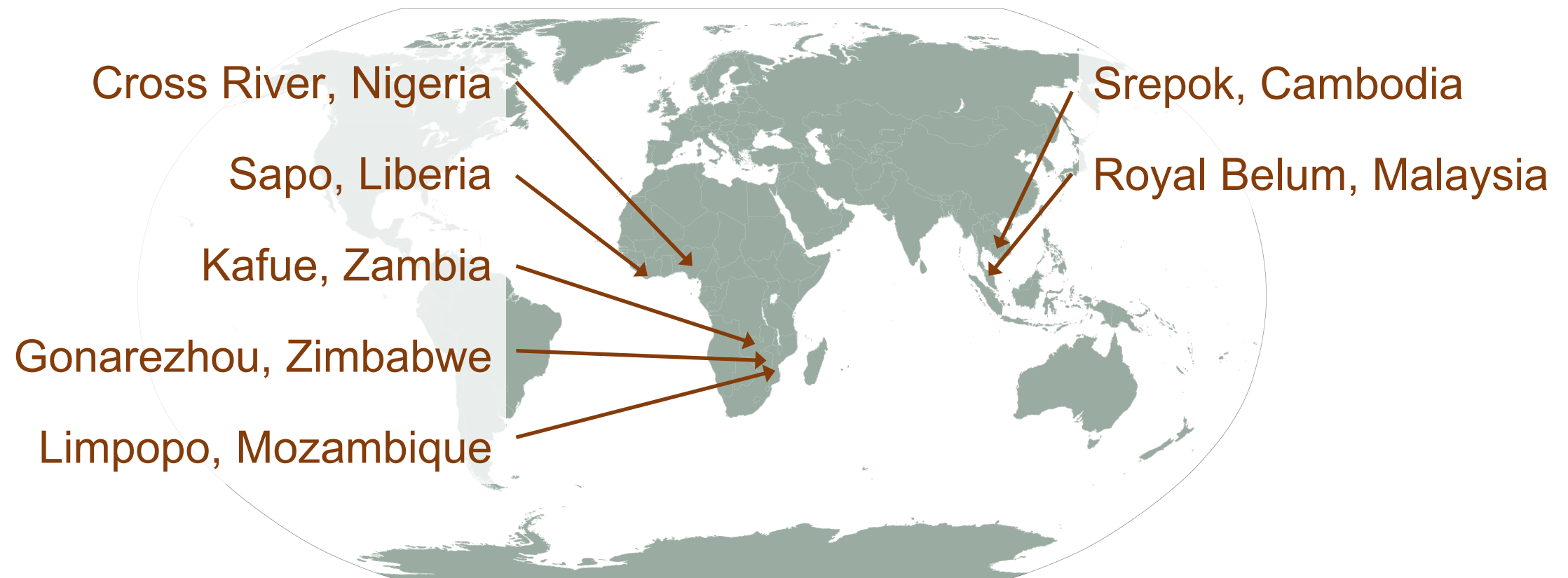
**2021 PAWS**

*1,000 snares found in March*

# PAWS GOES GLOBAL with SMART platform!!



**Protect Wildlife  
800 National Parks  
Around the Globe**



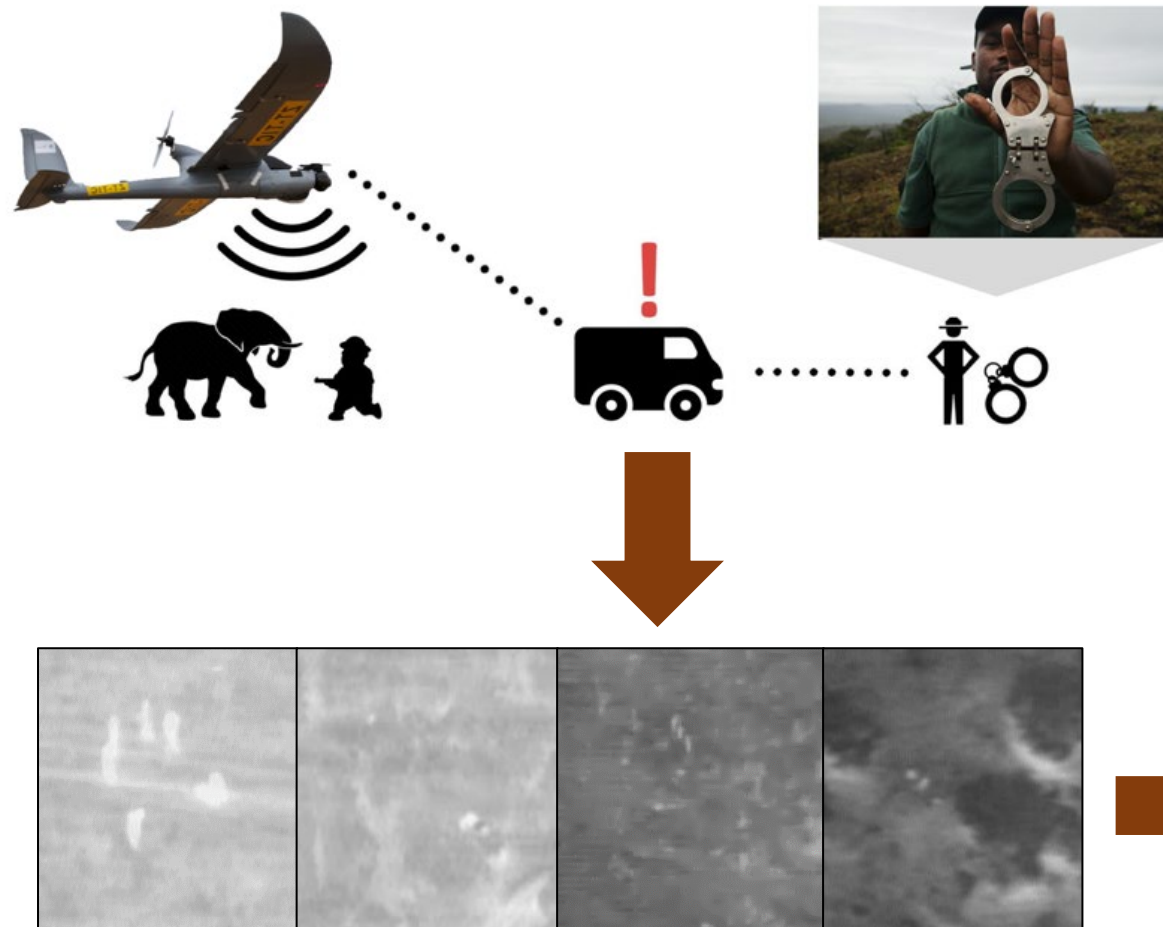


# Direction #1: Integrating Real-Time “SPOT” Information

(IAAI 2018)



Bondi



Goal: automatically find poachers

# Drone Used to Inform Rangers

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Xu



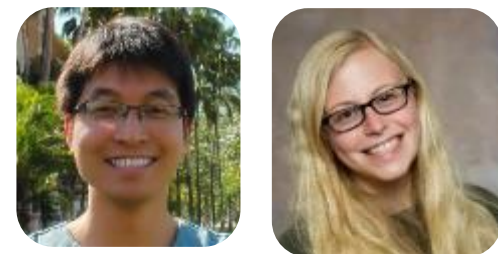
Bondi

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





# Drone Used to Inform Rangers



Xu



Bondi

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



# Drone Used to Inform Rangers



Xu



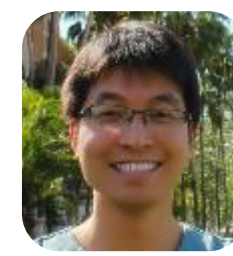
Bondi

- $Prob(ranger\ arrives) = 0.3$  [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, AAMAS 2021)



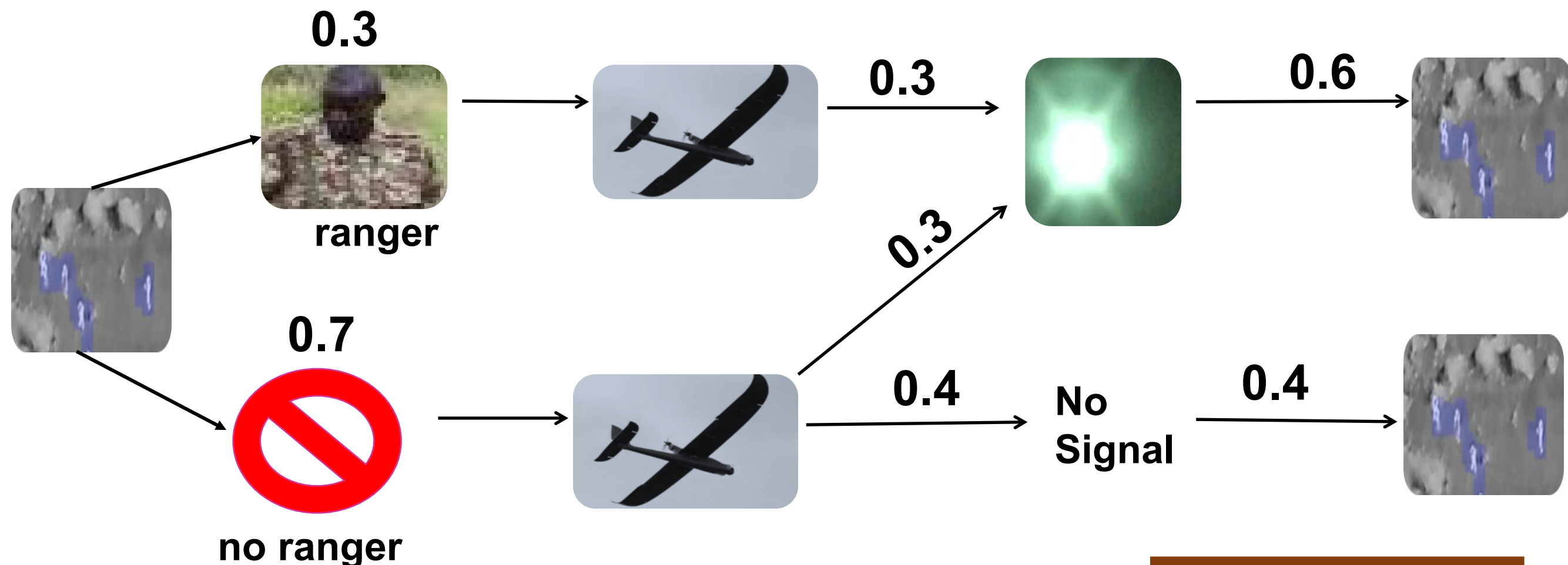
Xu



Bondi

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

- Poacher best interest to “believe signal” even if know 50% defender deception
- Recent work used RL for deception policy generation (AAMAS 2021)



# Future: AI for Social Impact (AI4SG or AI4SI)

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Achieving social impact & AI innovation go hand in hand



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



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

# 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)

@MilindTambe\_AI



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