



How to “AI for Social Good”: Case Studies in applying AI for Public Health & Conservation

MILIND TAMBE

Director “AI for Social Good”, Google Research India

&

Director Center for Research on Computation and Society, Harvard University

@MilindTambe_AI

AI and Multiagent Systems Research for Social Impact



Public Health



Conservation



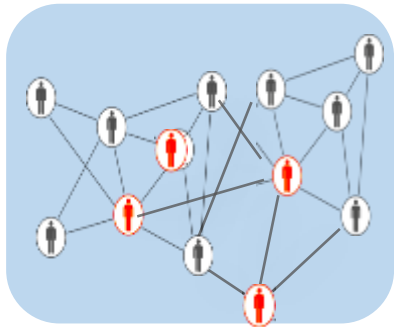
**Public Safety
and Security**

Viewing Social Problems as Multiagent Systems

Key research challenge across problem areas:

**Optimize Our Limited Intervention Resources
when
Interacting with Other Agents**

Optimizing Limited Intervention Resources



**Social
Networks &
Bandits**

Public Health



**Green
security
games**



Conservation



**Public Safety
& Security**



**Stackelberg
security
games**

Google Research Bangalore

AI for Social Good



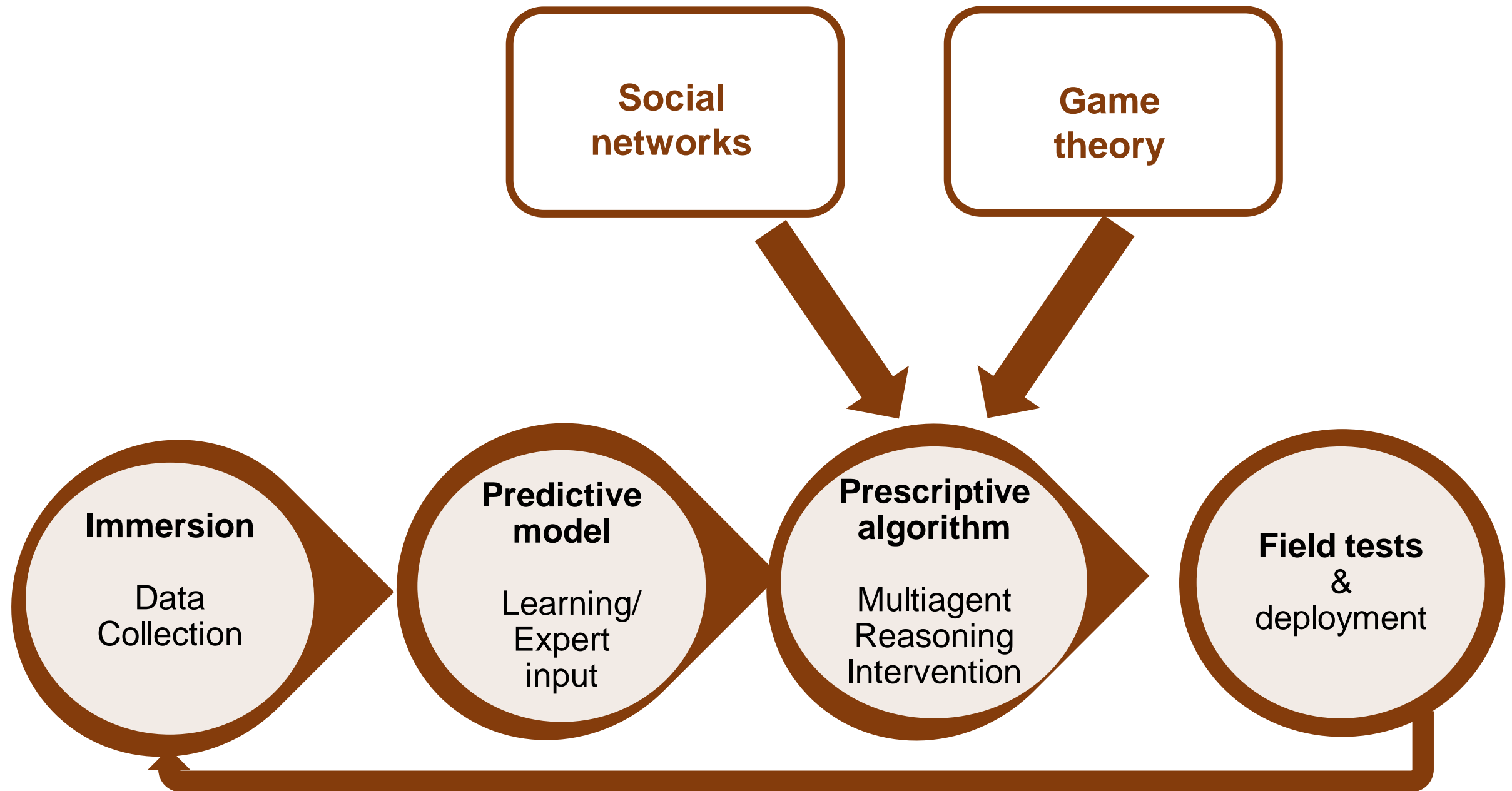
Public Health



Conservation

Three Common Themes

Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships

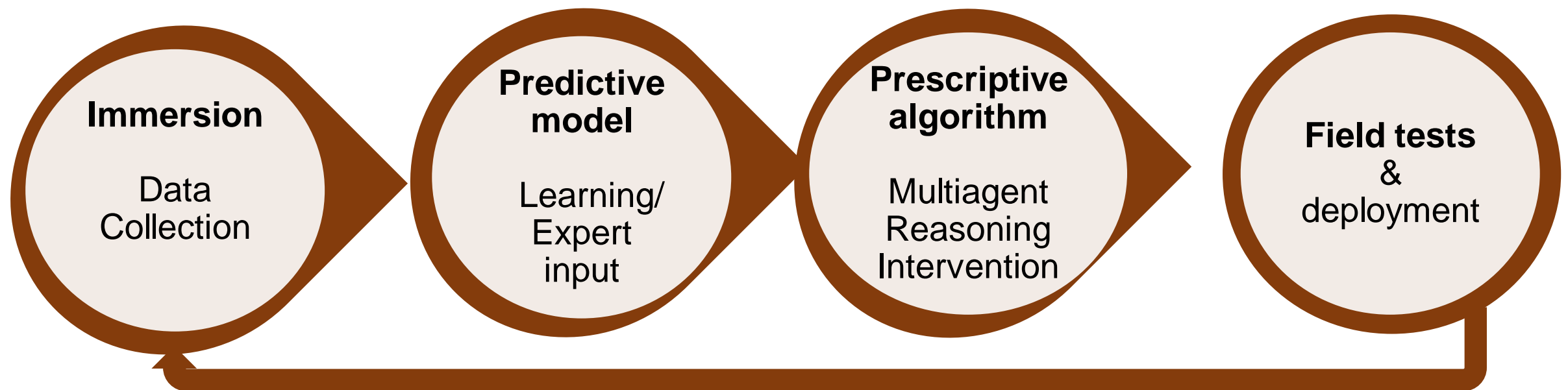


Three Common Themes

Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships

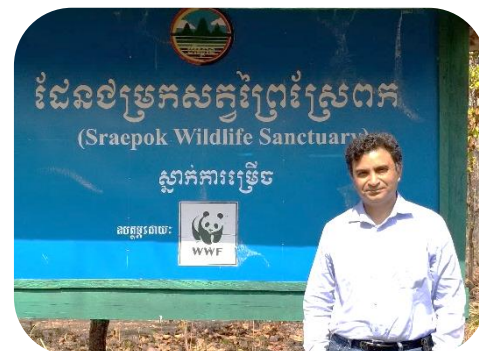
Field test & deployment: Social impact is a key objective

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



Three Common Themes

Multiagent systems, Data-to-deployment pipeline, Interdisciplinary partnerships



ASHOKA TRUST FOR RESEARCH IN
ECOLOGY & THE ENVIRONMENT

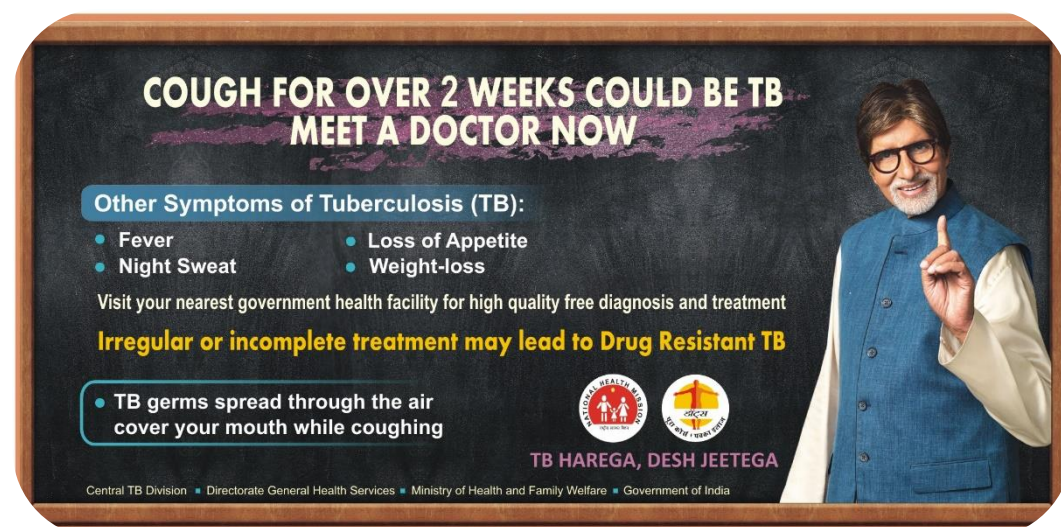


Three Key Takeaways: AI4SG

What are key problem types for AI for Social Good in public health & conservation?

What are some key AI research challenges (pay attention to models, not details)

How do we launch projects in AI for Social Good?



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

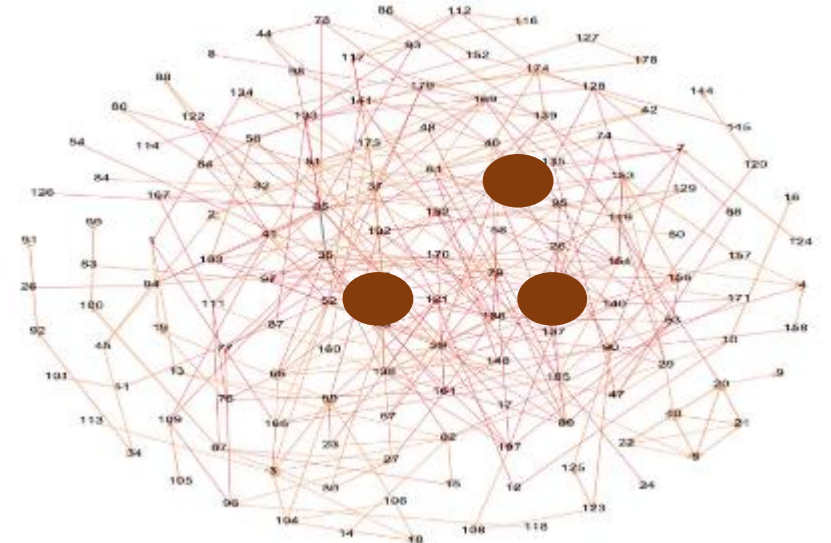
Preventing HIV in homeless youth: Rates of HIV 10 times housed population

- **Shelters:** Limited number of peer leaders to spread HIV information in social networks
- “Real” face-to-face interactions; not Facebook etc
- Other applications: HIV prevention (SWASTI), Tuberculosis awareness...

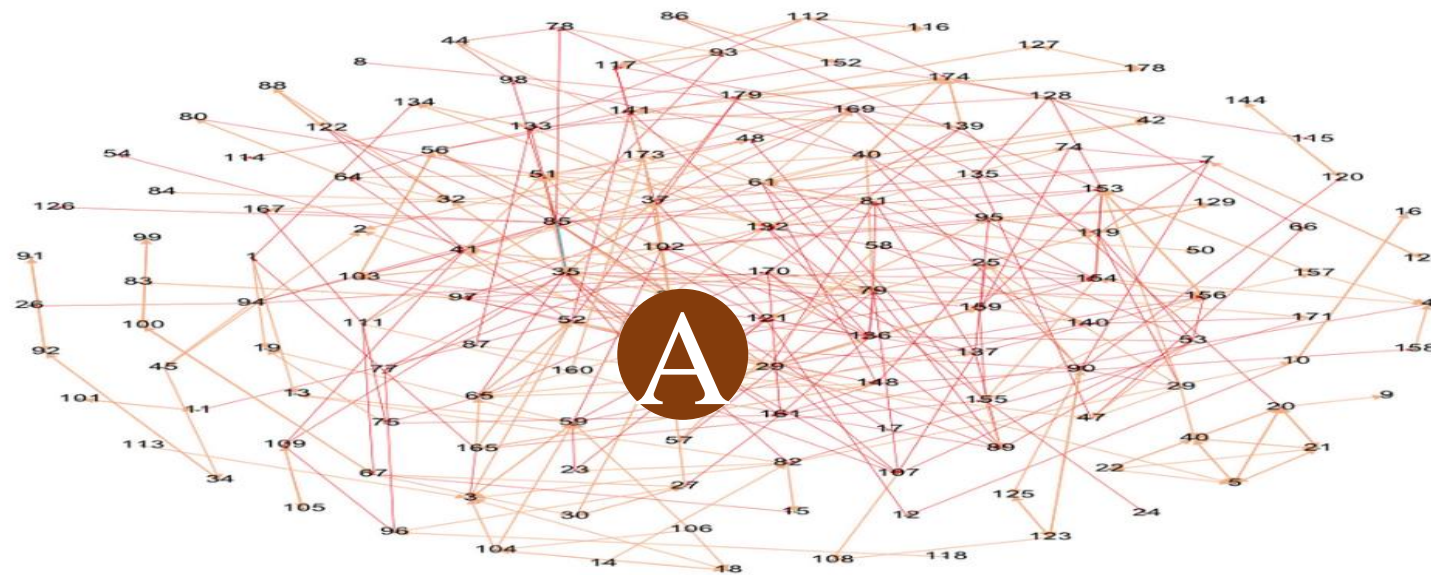


Influence Maximization in Social Networks

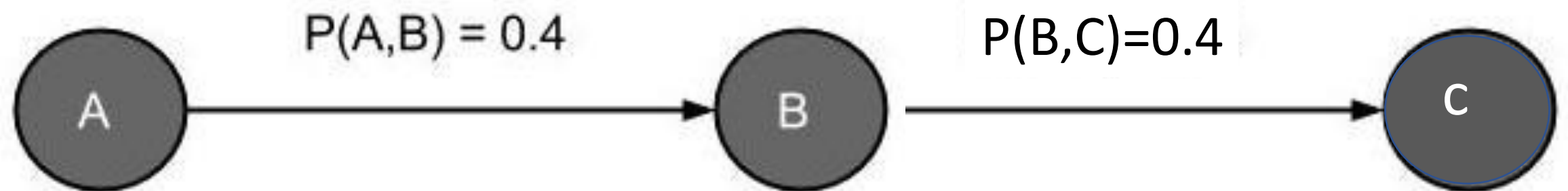
- Given:
 - Social network Graph G
 - Choose K “peer leader” or influencer nodes
 - Assume: Independent cascade model of information spread
- Objective:
 - Maximize expected number of influenced nodes



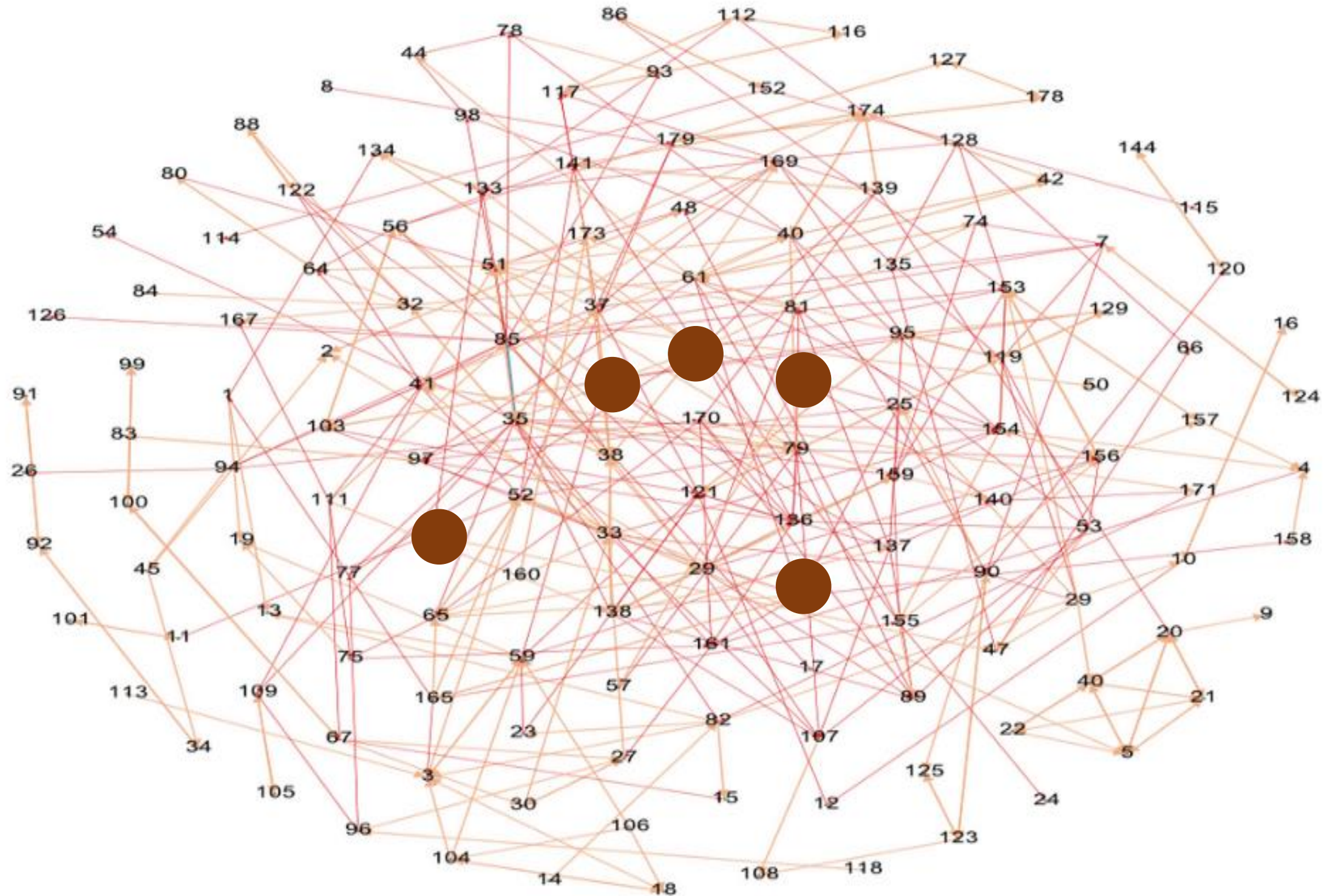
Independent Cascade Model



- Propagation Probability (for each edge)



Influence Maximization (Budget = 5 nodes)





Influence Maximization in Social Networks

Three Key Challenges Combined Together

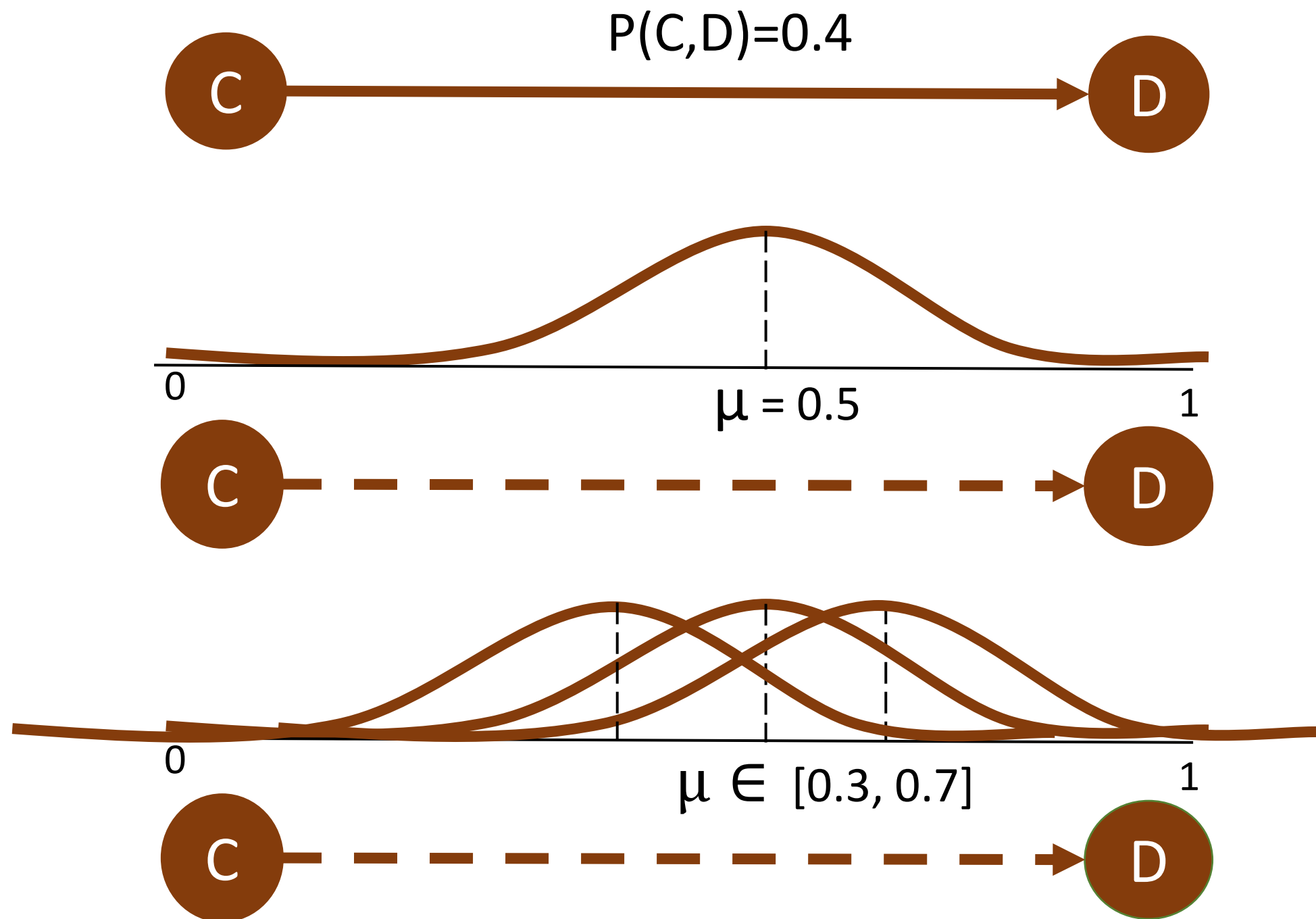
Research challenges in AI for social good?

Lack of data & uncertainty is a feature (research challenge), not a bug

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

Focus on the key idea; mathematical details read papers later

Challenge 1: Uncertainty in Real-world Physical Social Networks



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

μ, σ

HEALER Algorithm

Robust Influence Maximization

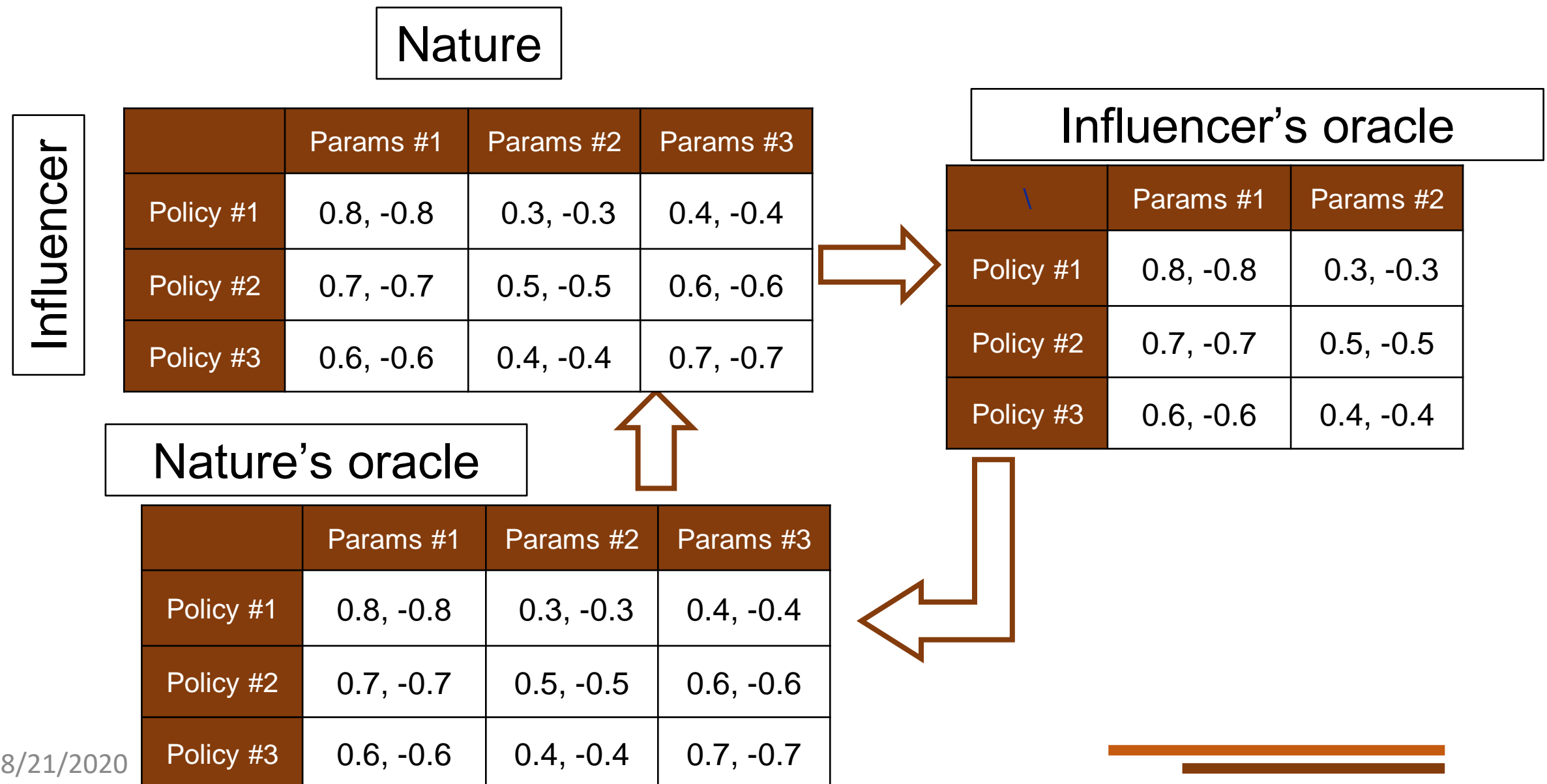
(AAMAS 2017)



Wilder

Theorem: Converge with approximation guarantees

- Equilibrium strategy despite exponential strategy spaces: Double oracle



Challenge 2: Multi-step Policy

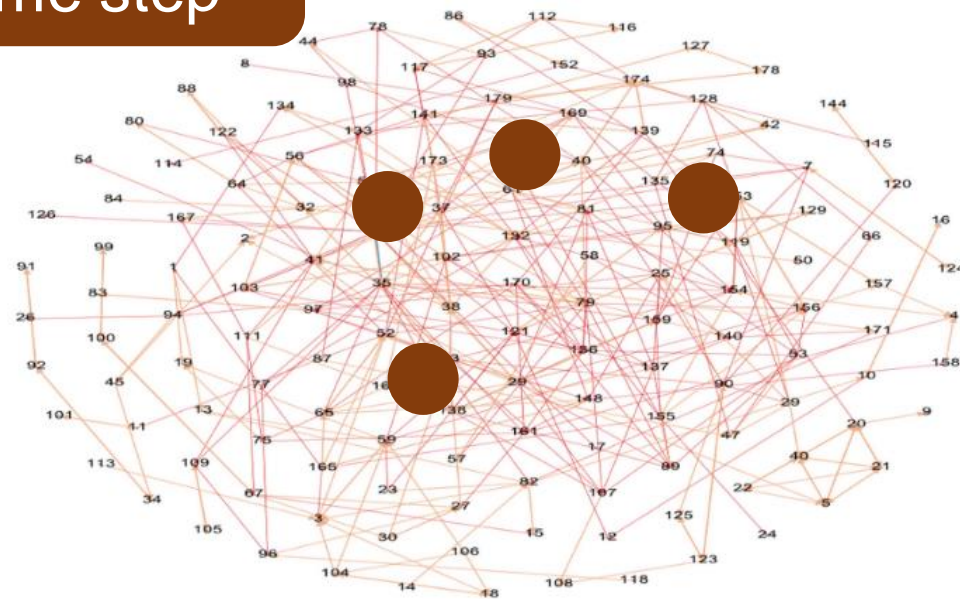


Yadav

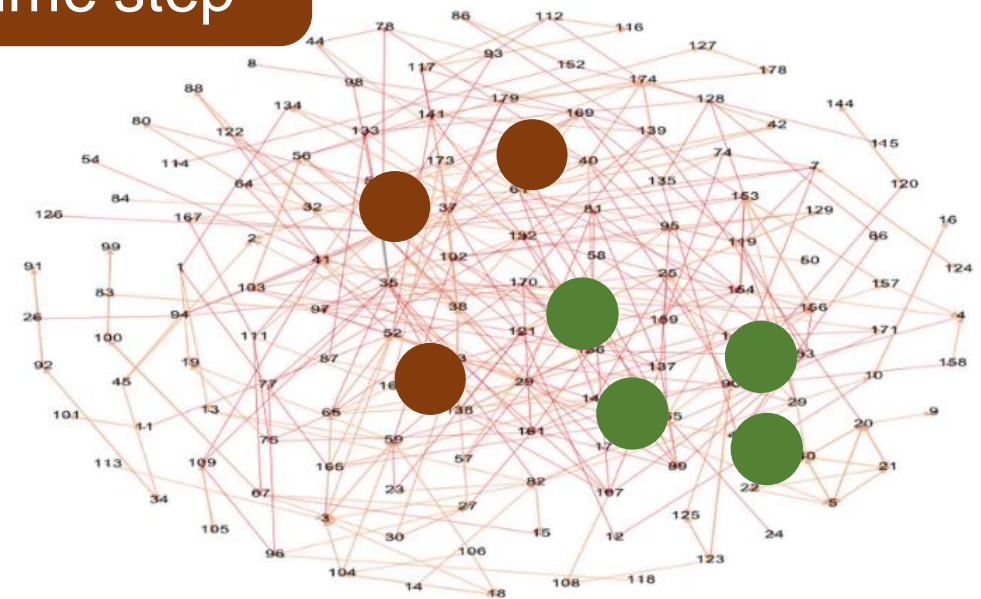


Wilder

$K = 4$
1st time step



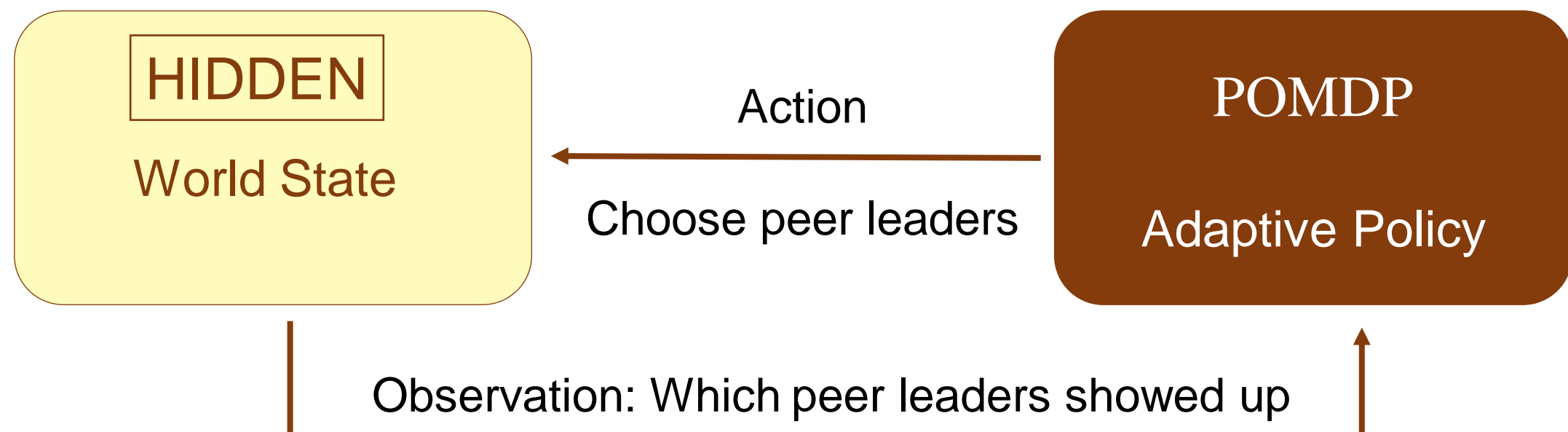
$K = 4$
2nd time step



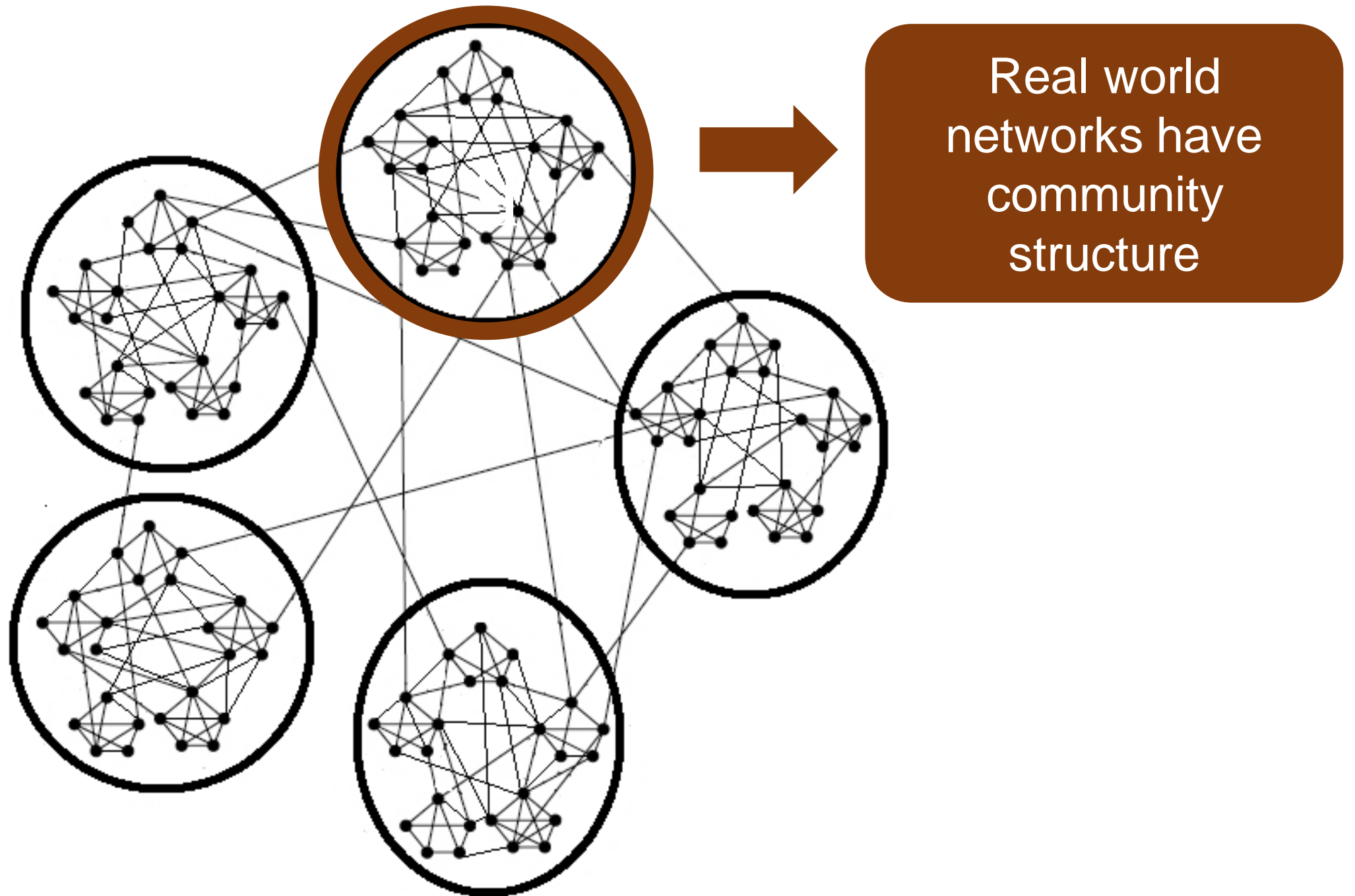
- History: $\{(Invited-at-time1, absent-at-time1), (Invited-at-time2, absent-at-time2), \dots\}$
- Provide policy $p: History(t) \rightarrow Invite \text{ peer leaders for } t+1$
- State of network is unobservable

POMDP (Partially Observable Markov Decision Problem)

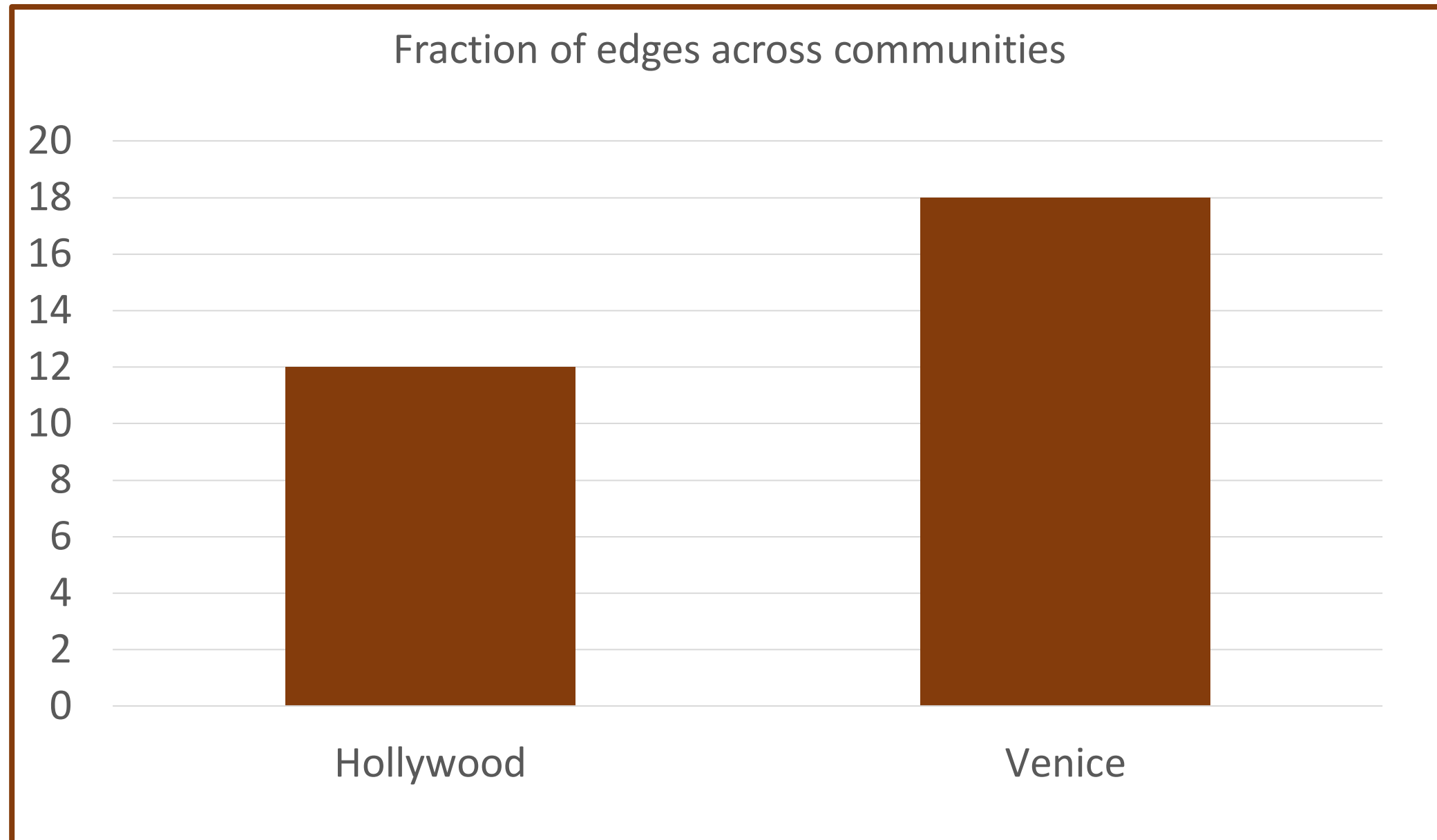
- ❑ Sequential decision making under uncertainty
 - ❑ Homeless shelters – sequentially select nodes
- ❑ Environment state not fully observable to agent
 - ❑ Homeless shelters – network state not known



Graph Partitioning: POMDPs Expensive to Solve



Graph Partitioning

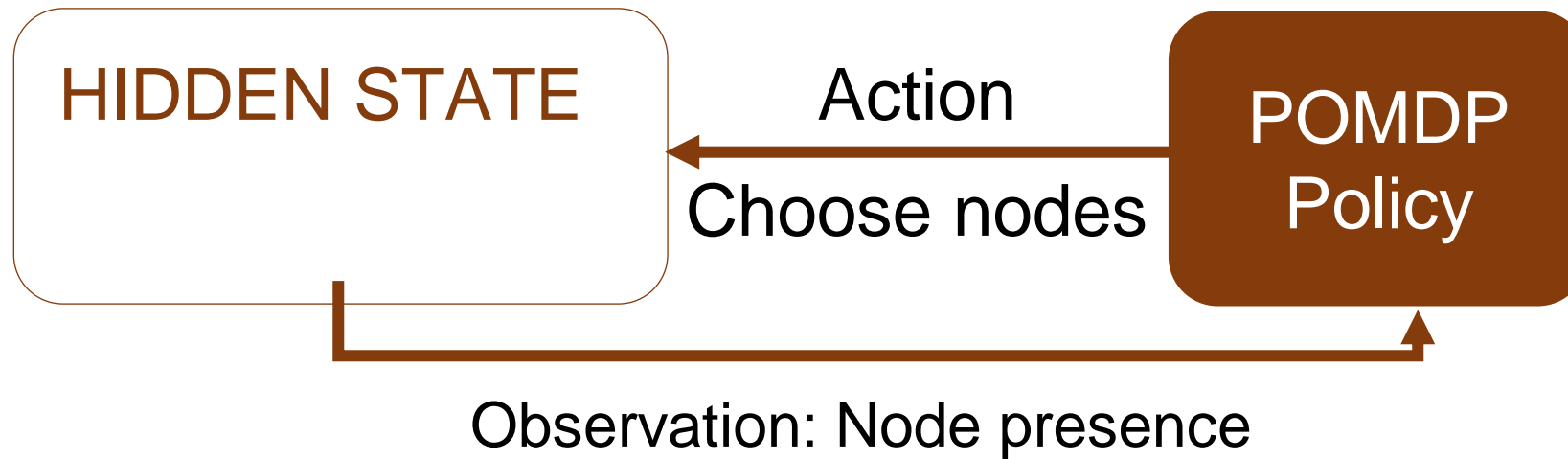


POMDPs for Multi-Step Policy for Robust, Dynamic Influence Maximization

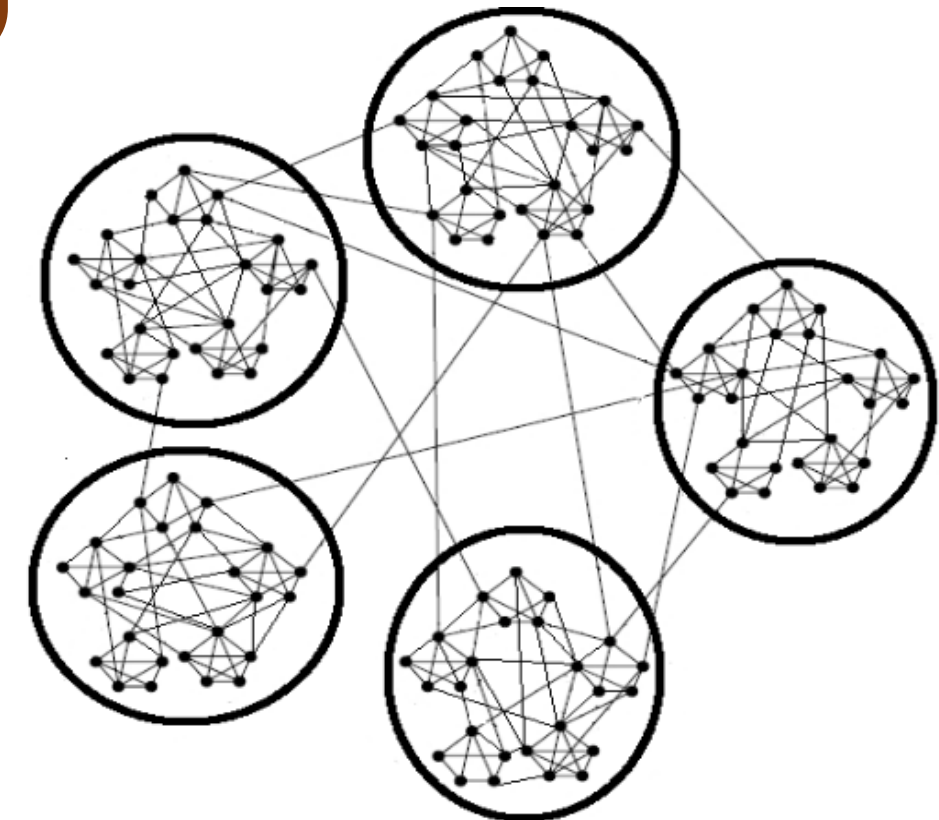
(AAMAS 2018a)



Yadav



Adaptive Policy



Partition POMDPs:
Exploit community
structure

Challenge 3: Sampling to avoid Data Collection Bottleneck

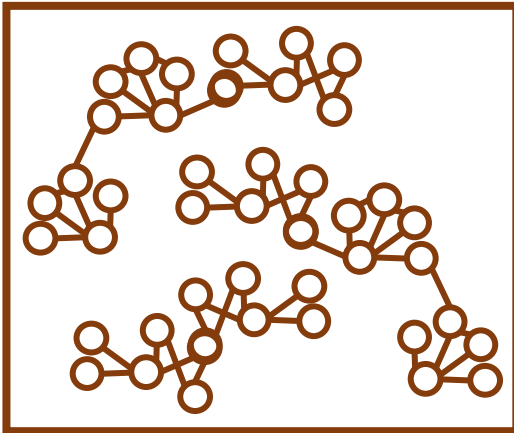
(AAAI 2018)



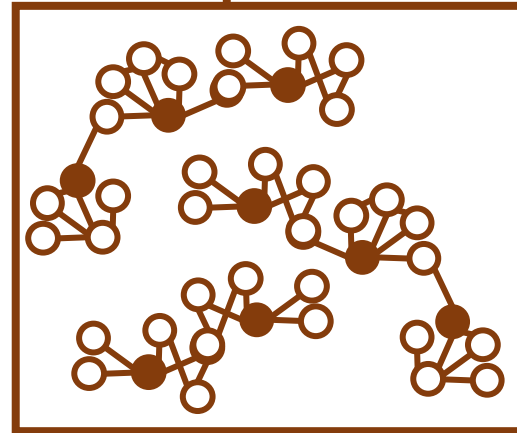
Wilder

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

Data collection costly



Sample 20%



Sampling Algorithm

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

- Input: total number of nodes, n
- Sampling algorithm queries upto query budget
- Output K seed nodes; spread influence via independent cascade model
- Compare to OPT , best influence spread by algorithm with full network

(*)Community structured: drawn from a stochastic block model

Date: 8/21/2020

“Sampling-HEALER”

Pilot tests with 230 Homeless Youth

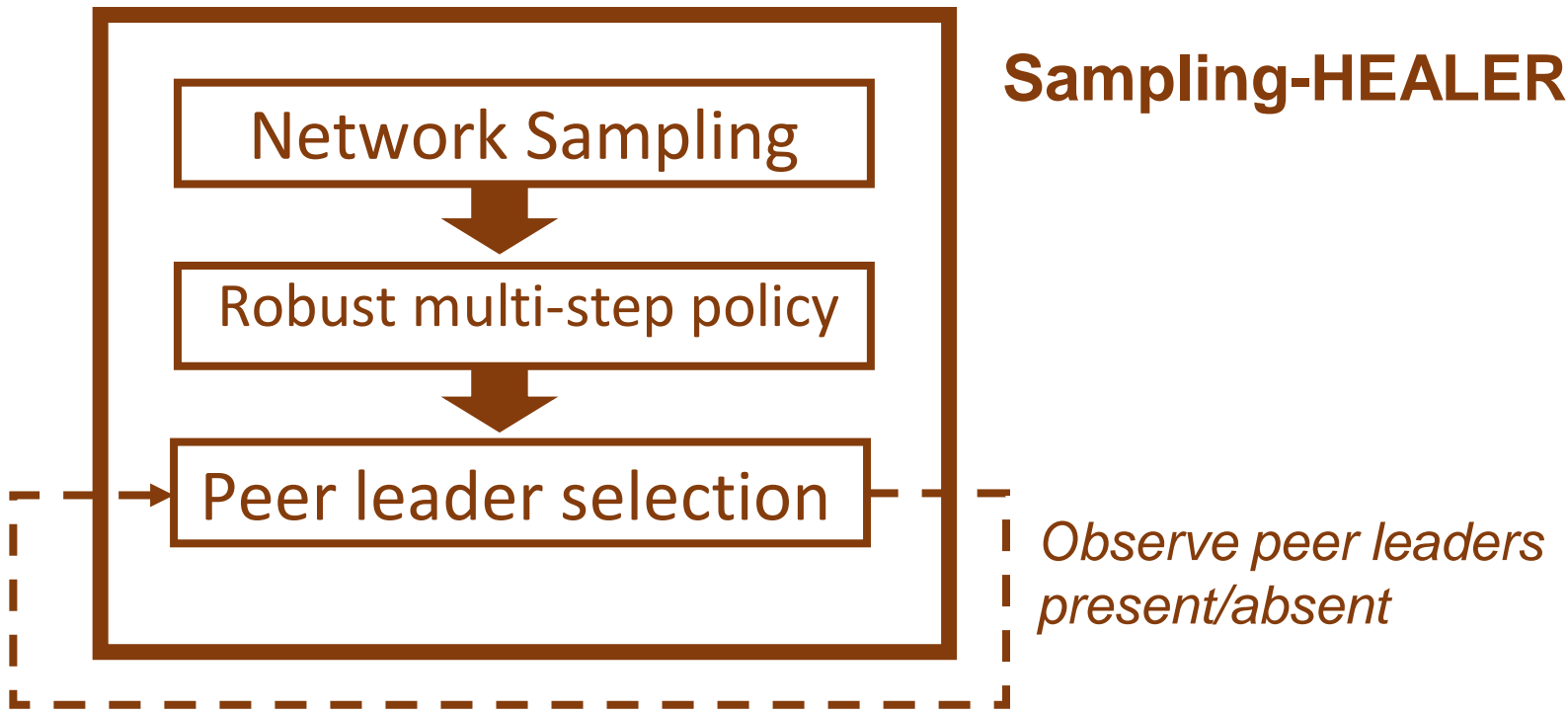
(IJCAI 2018)



Yadav



Wilder



12 peer leaders

Sampling HEALER (Sampled Network)	HEALER (Full Network)	HEALER+ (Full Network)	DEGREE CENTRALITY (Full Network)
60 youth	62 youth	56 youth	55 youth

Results: Pilot Studies

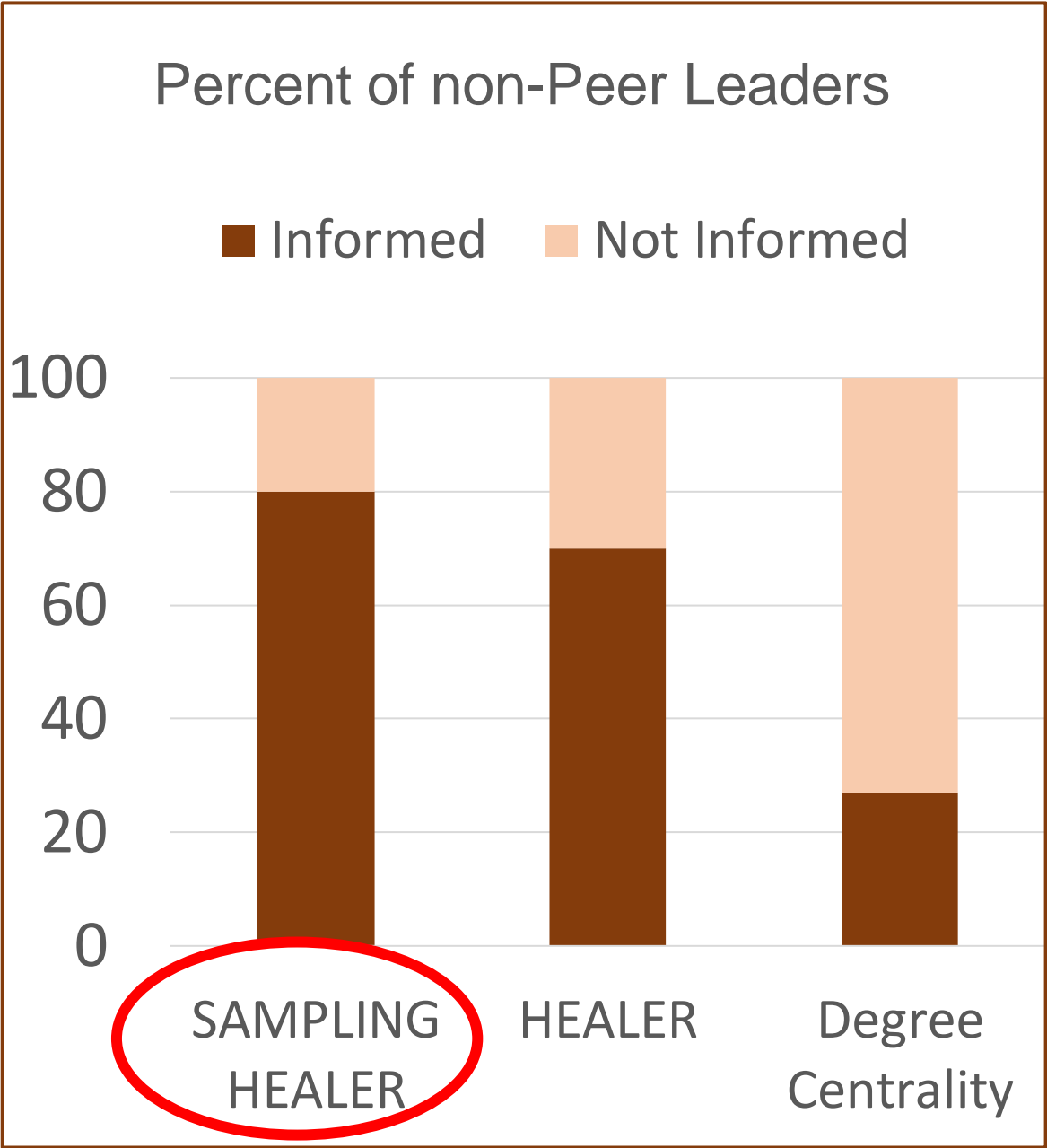
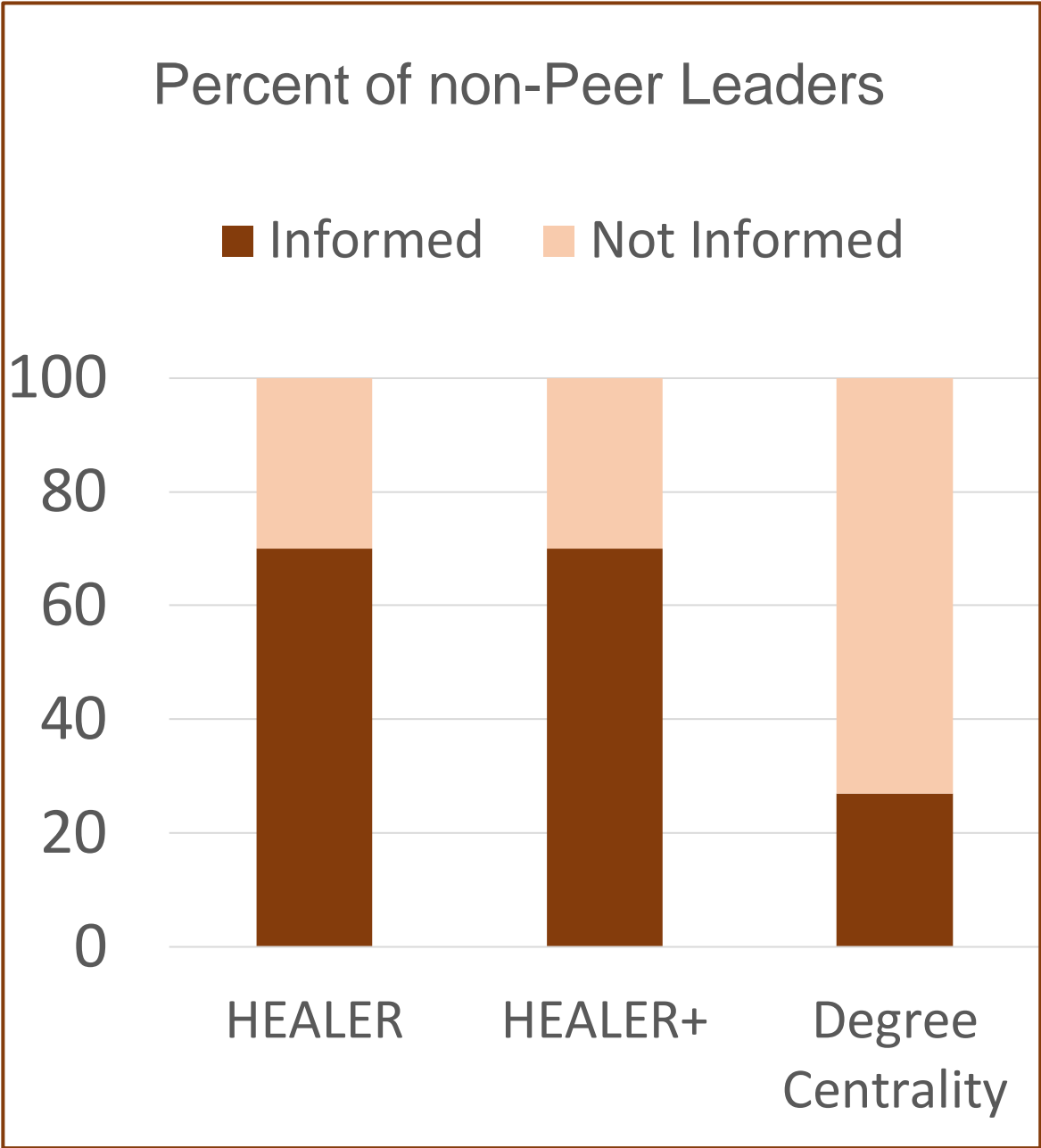
(Journal of Society of Social Work & Research 2018)



Yadav



Wilder



Results of 800 Youth Study [with Prof. Eric Rice]

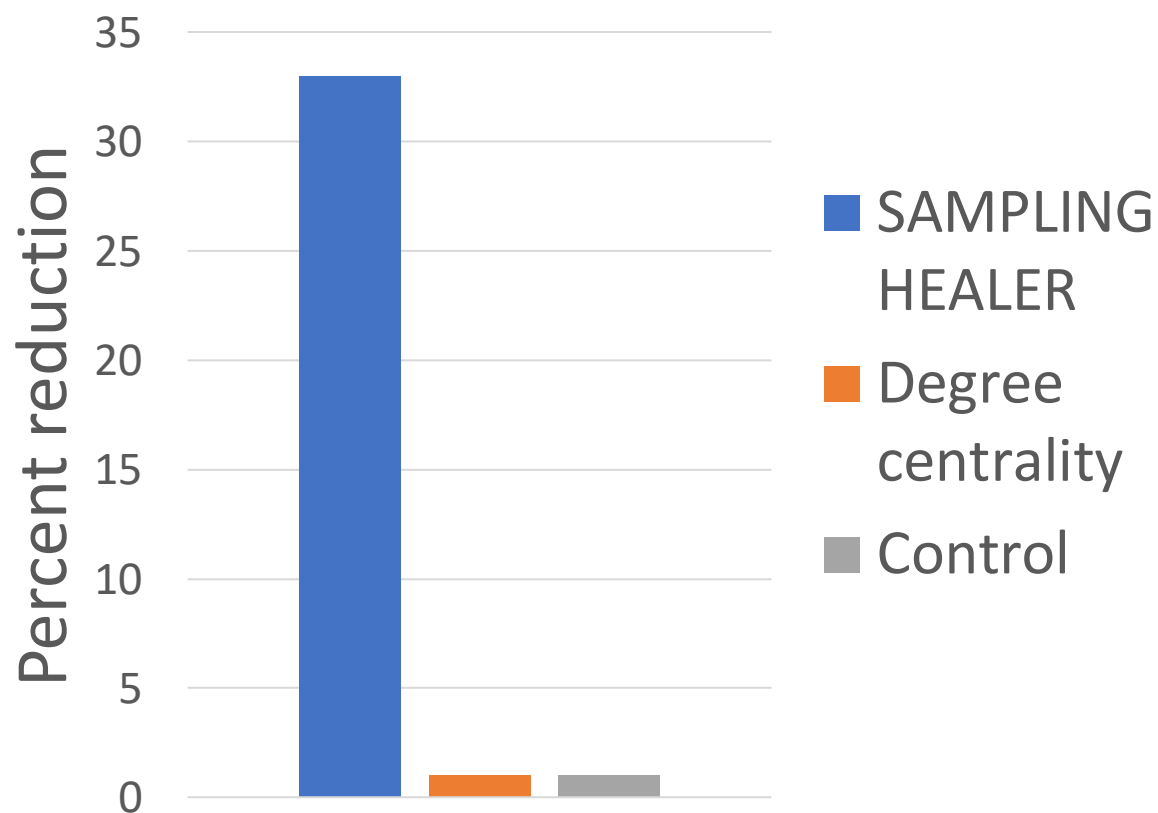
Actual Change in Behavior?

(Under submission)

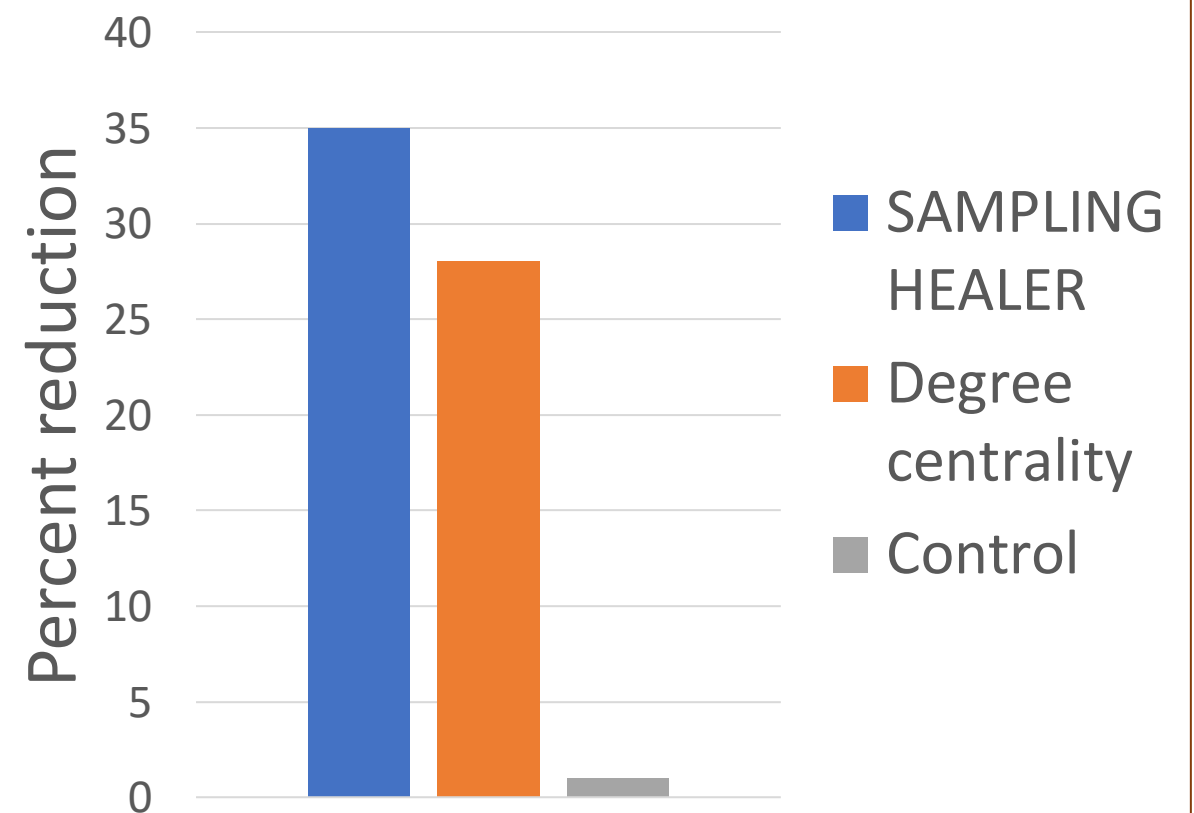
First large-scale application of influence maximization for public health



Reduction in condomless anal sex (1 month)



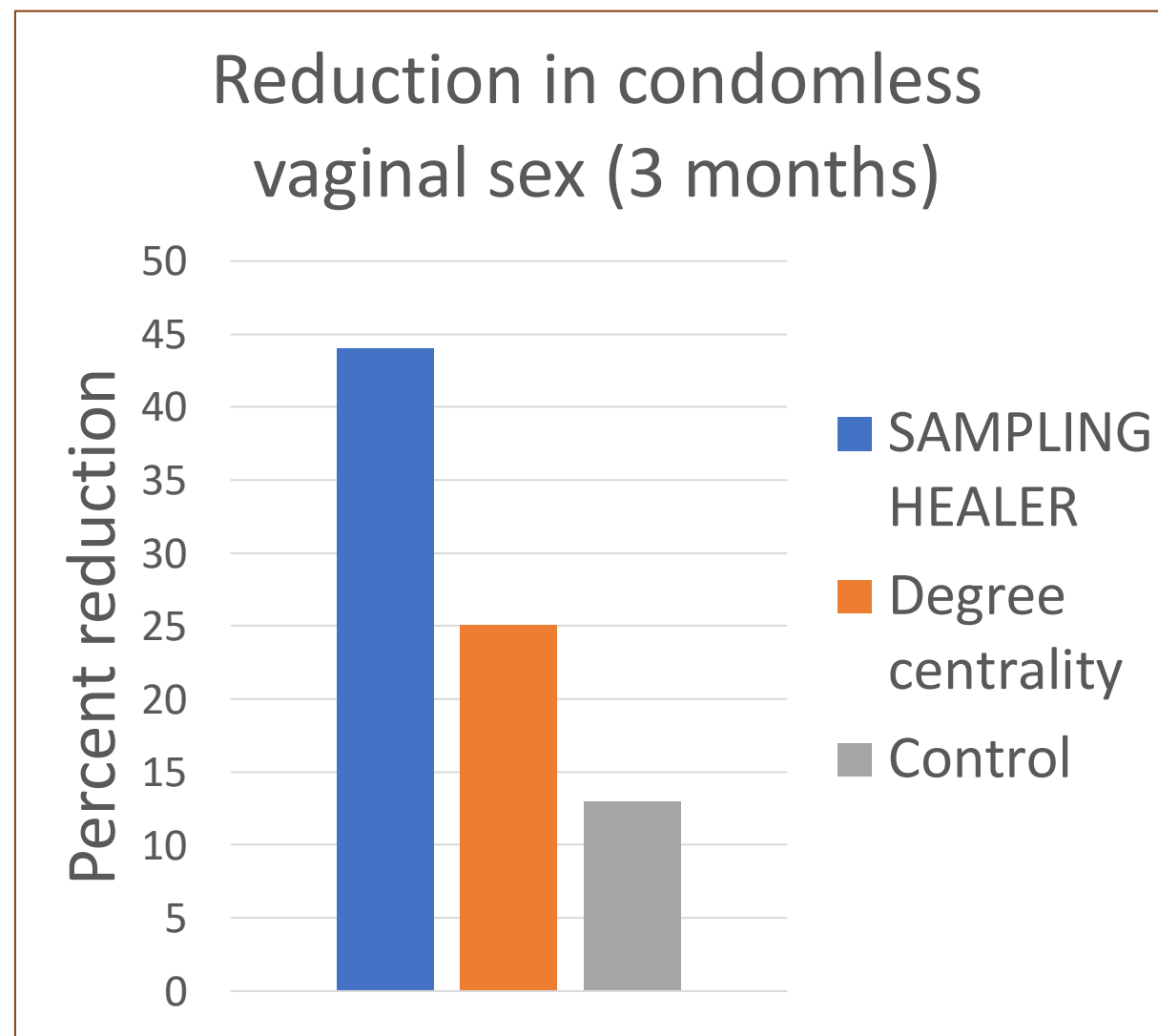
Reduction in condomless anal sex (3 months)



Results of 800 Youth Study [with Prof. Eric Rice]



LOS
ANGELES
LGBT
CENTER

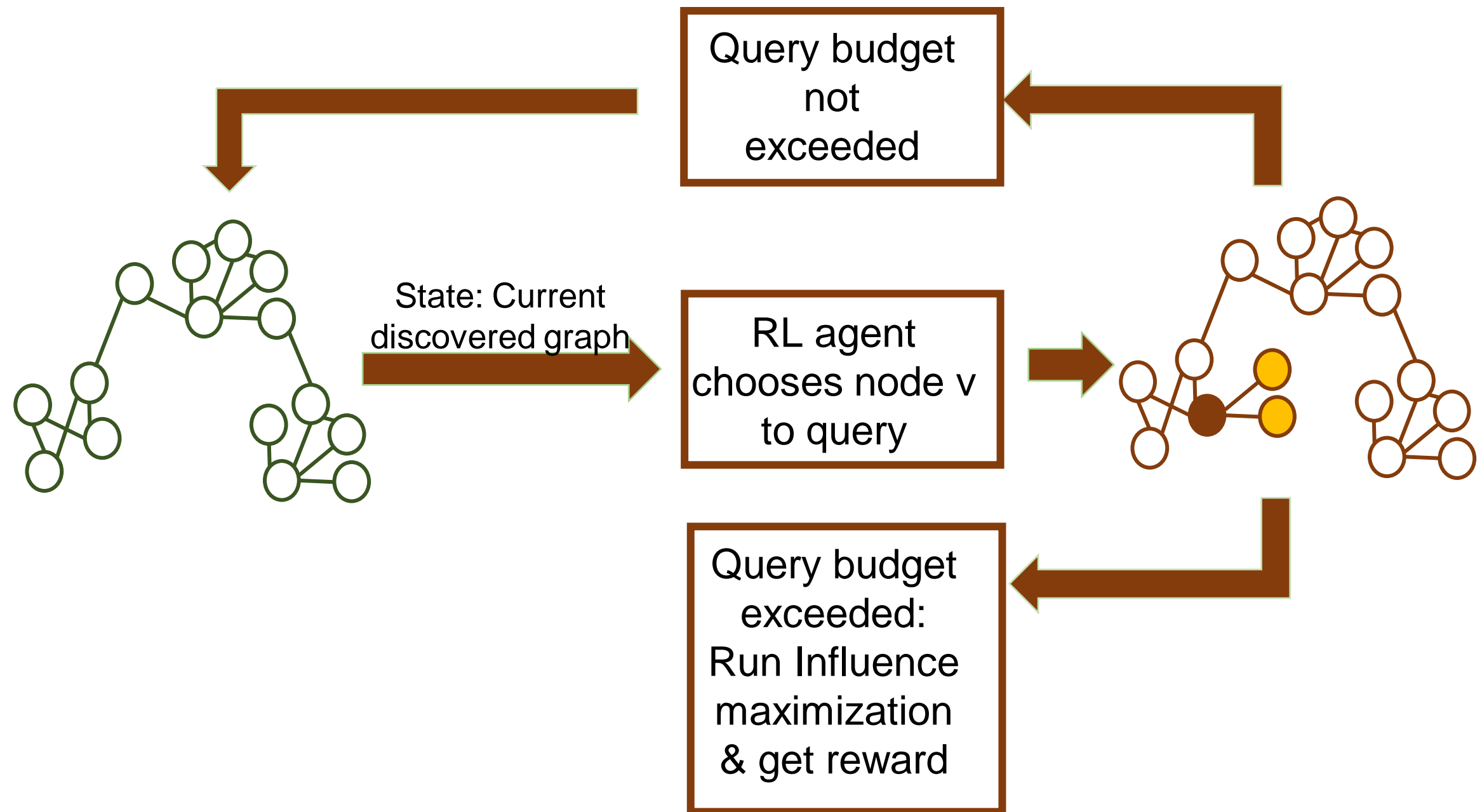


AI Assistant: HEALER



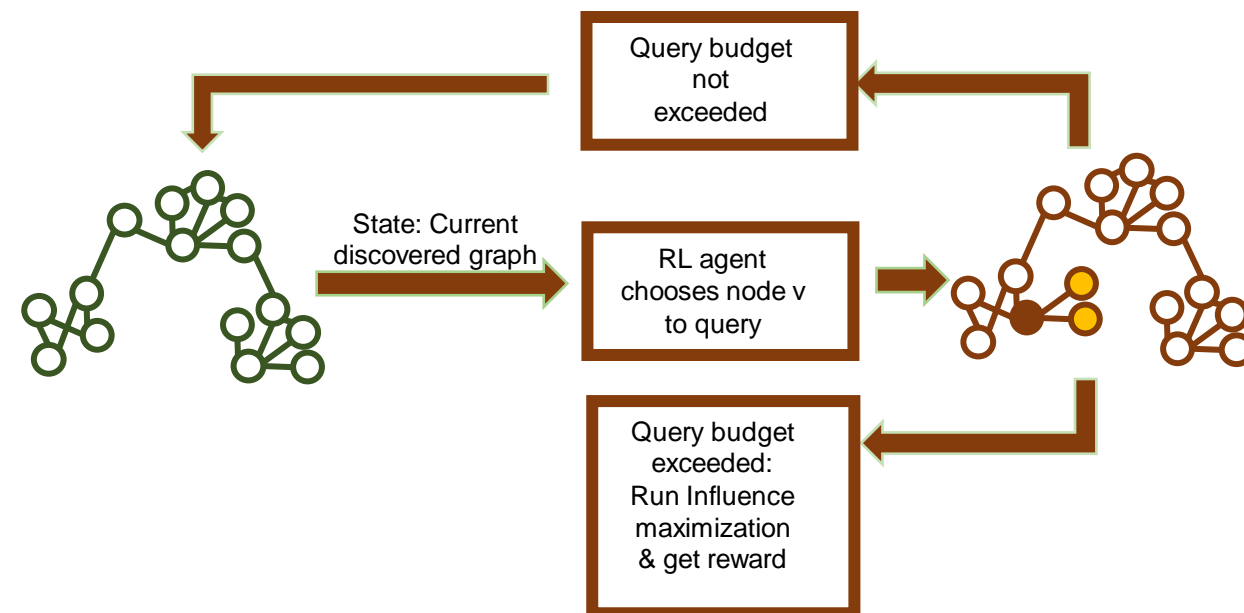
Next steps: Data to Deployment Pipeline Using an RL agent?

(with B. Ravindran & team, AAMAS 2020)



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

How Did the Projects Get Launched

.

Collaboration of

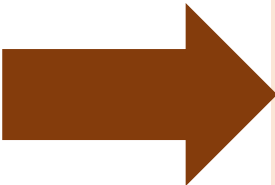
AI researchers, Social work researchers, Homeless Shelters

**Started via discussion with social work professor:
Focused on problem, rather than starting with a solution approach**

Support as academics: Will provide AI expertise

Outline

Public Health

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

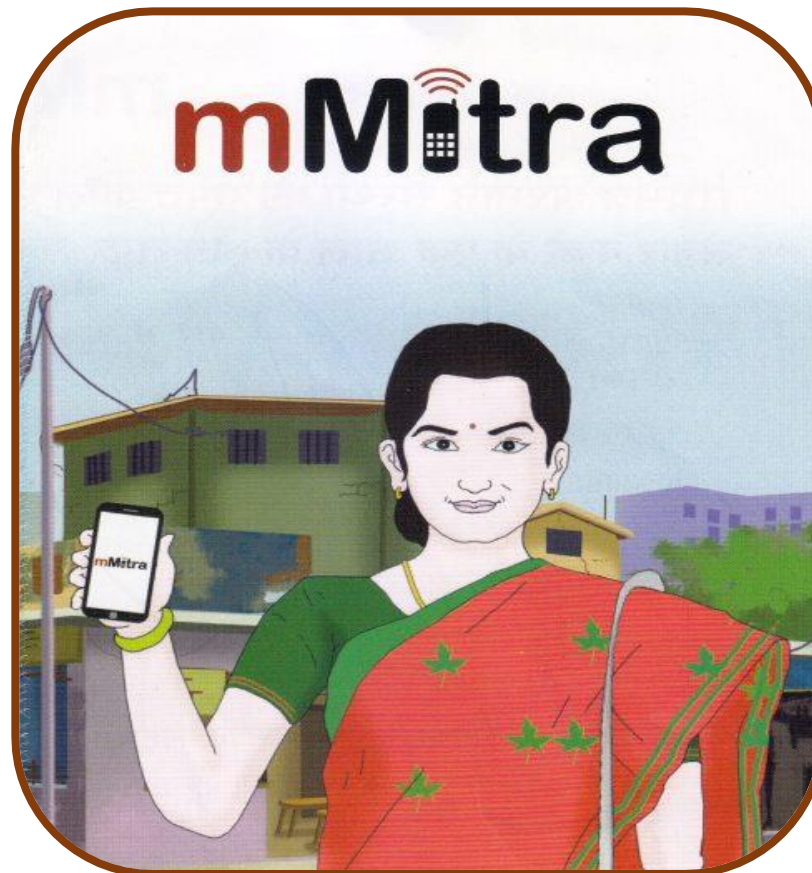
Conservation

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*

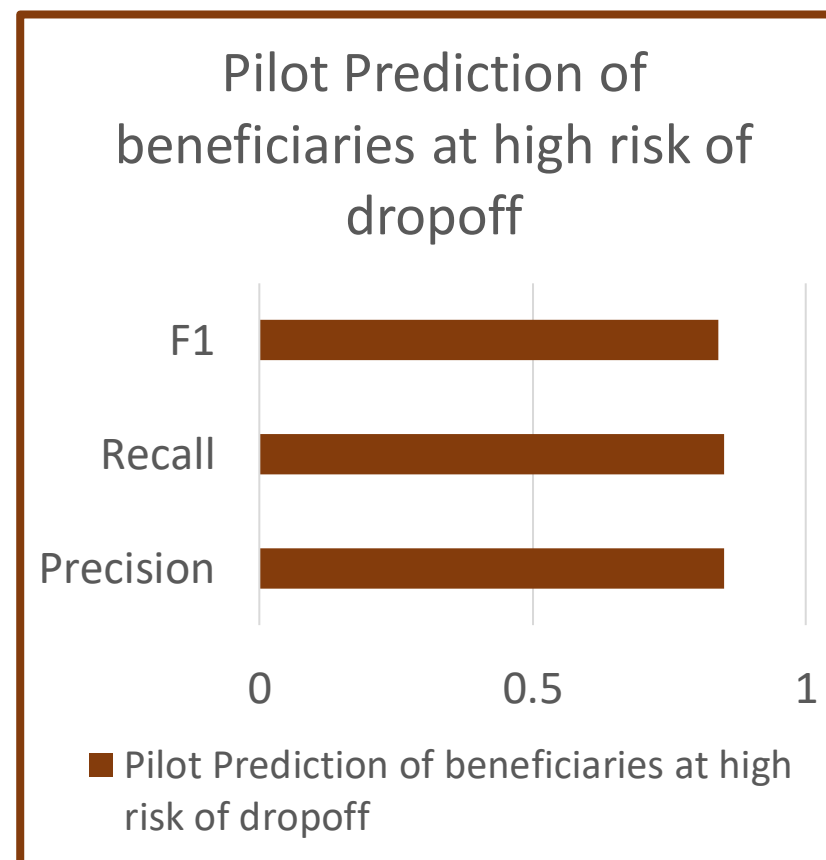
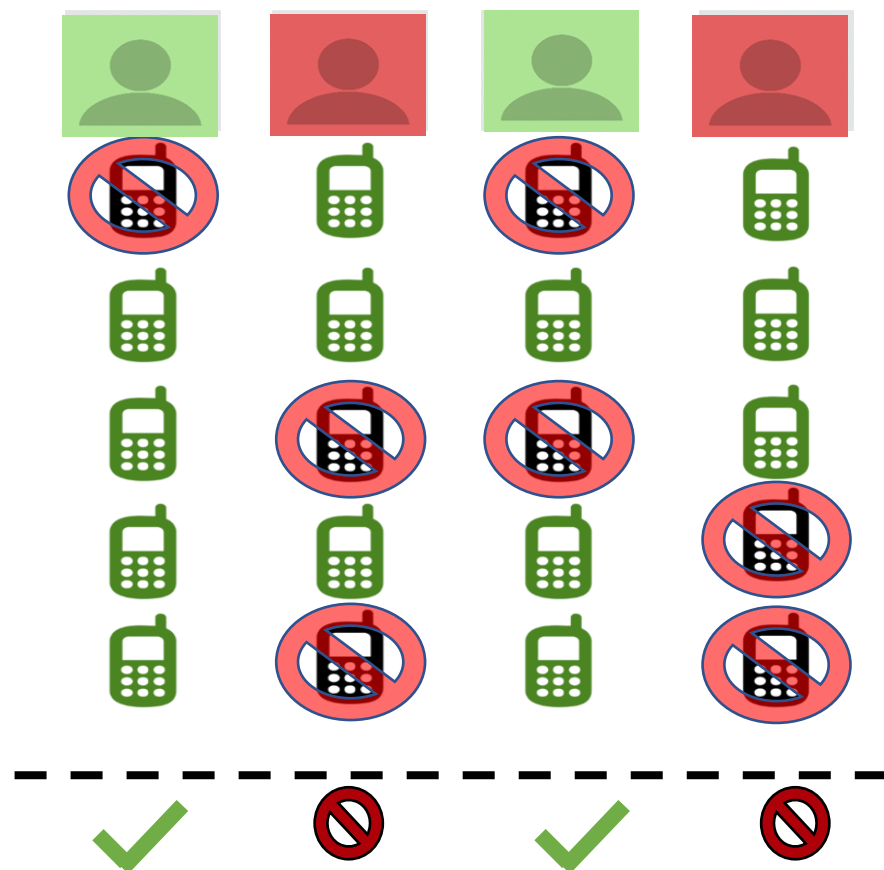


Passive Adherence Monitoring Maternal & Child Care in India

(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**



ARMMAN Pilot

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

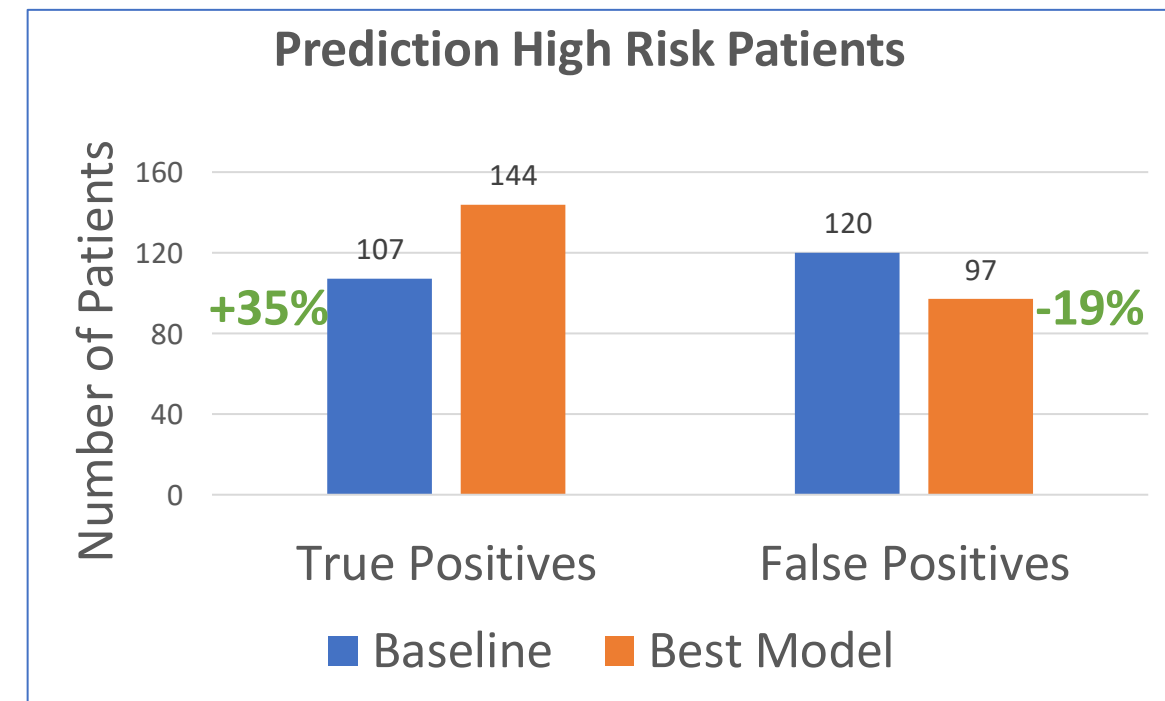
Passive Adherence Monitoring Preventing Tuberculosis in India

(KDD 2019)

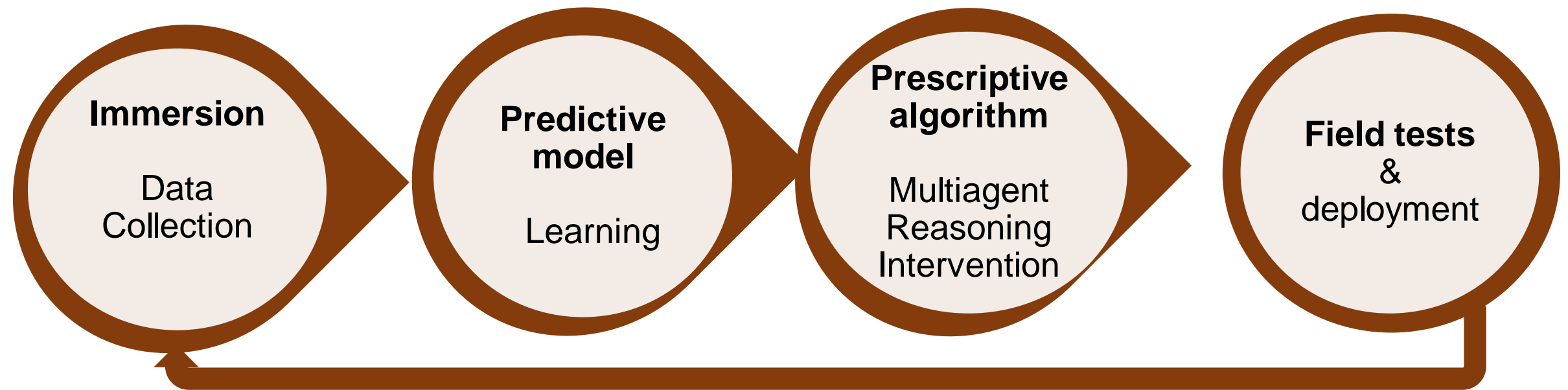


Tuberculosis (TB): ~500,000 deaths/year, ~3M infected in India

- *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*



Intervention Reasoning: Active Adherence Monitoring



Health worker calls, patients do not call

Intervention Scheduling with Scarce Data: Passive vs Active Adherence Monitoring

(Under submission)



Mate

Killian

Health worker

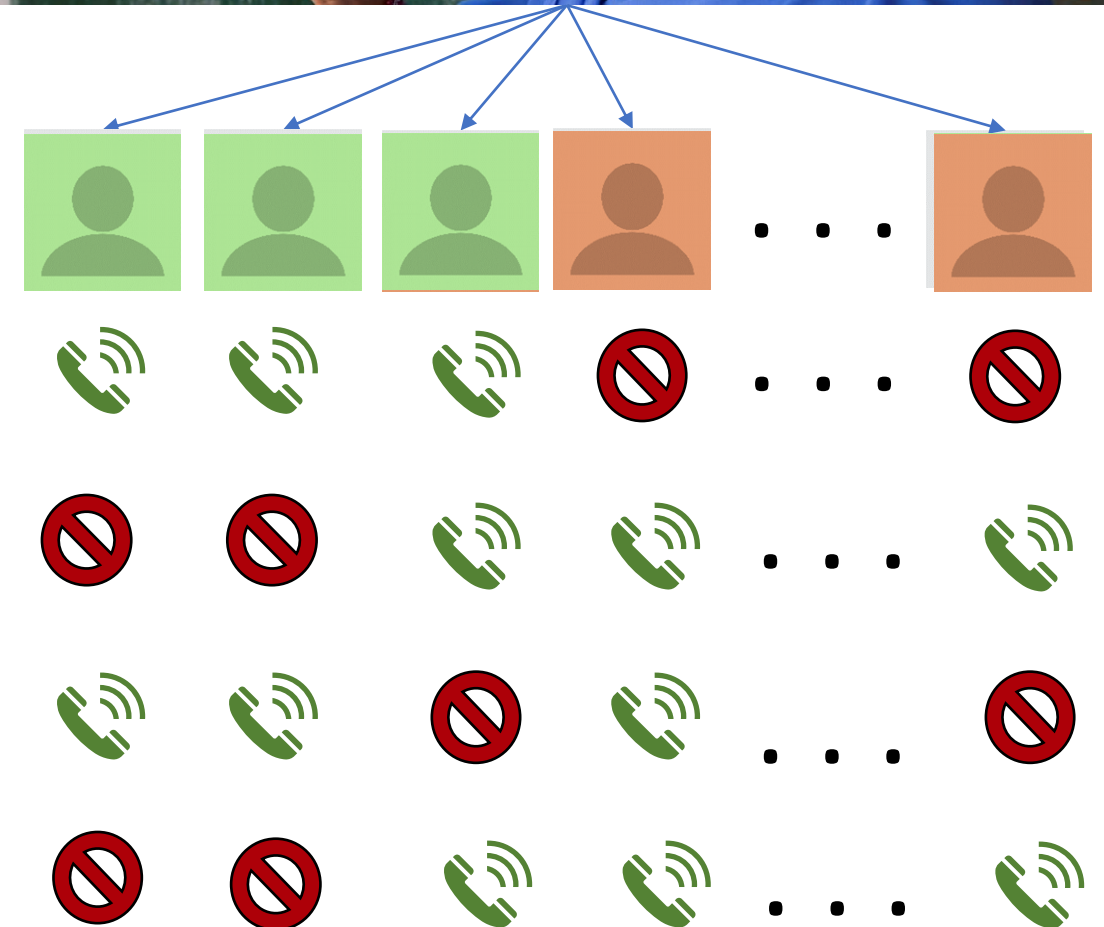
Call patients: Track, improve adherence

Challenge:

- *Large number of patients (N)*
- *Which 'k' patients to call?*

Approach:

- *Adherence Restless Bandits*



Intervention Scheduling with Scarce Data: Adherence Restless Bandits(A-RMAB)

(Under submission)



Mate

Killian

Restless multiarmed bandits (RMAB)

Adherence RMAB (A-RMAB):

- *Each arm has binary latent state $\{0, 1\}$*
- *0= not-adhering; 1= adhering*

	<i>not-adhering</i> <i>adhering</i>	
<i>not-adhering</i>	0.90	0.10
<i>adhering</i>	0.05	0.95

Intervention Scheduling with Scarce Data: Adherence Restless Bandits(A-RMAB)

(Under submission)



Restless multiarmed bandits (RMAB)

Adherence RMAB (A-RMAB):

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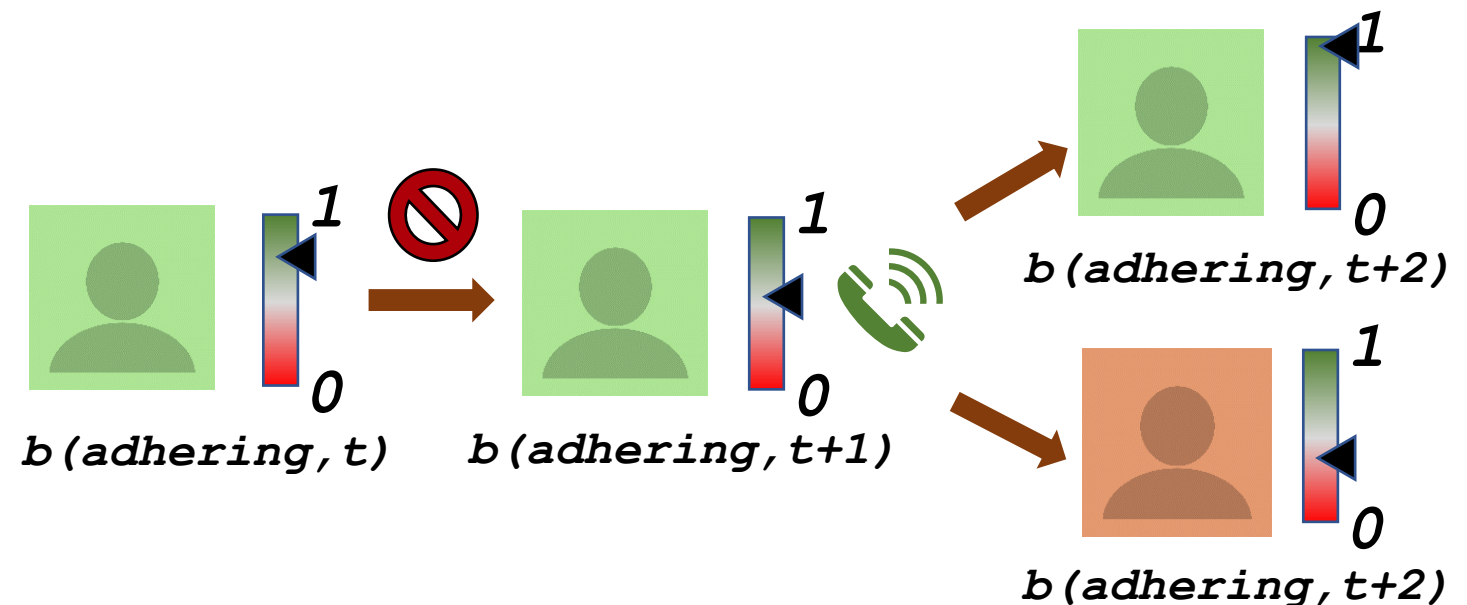
When arm not played

- No observation
- Instead, compute belief of adherence

When arm is played

- Observe current state
- Higher chance of adhering next round

	not-adhering	adhering
not-adhering	0.90	0.10
adhering	0.05	0.95



$$P(\text{adhering} \mid \text{call}) > P(\text{adhering} \mid \text{no call})$$

Intervention Scheduling with Scarce Data: Adherence Restless Bandits(A-RMAB)

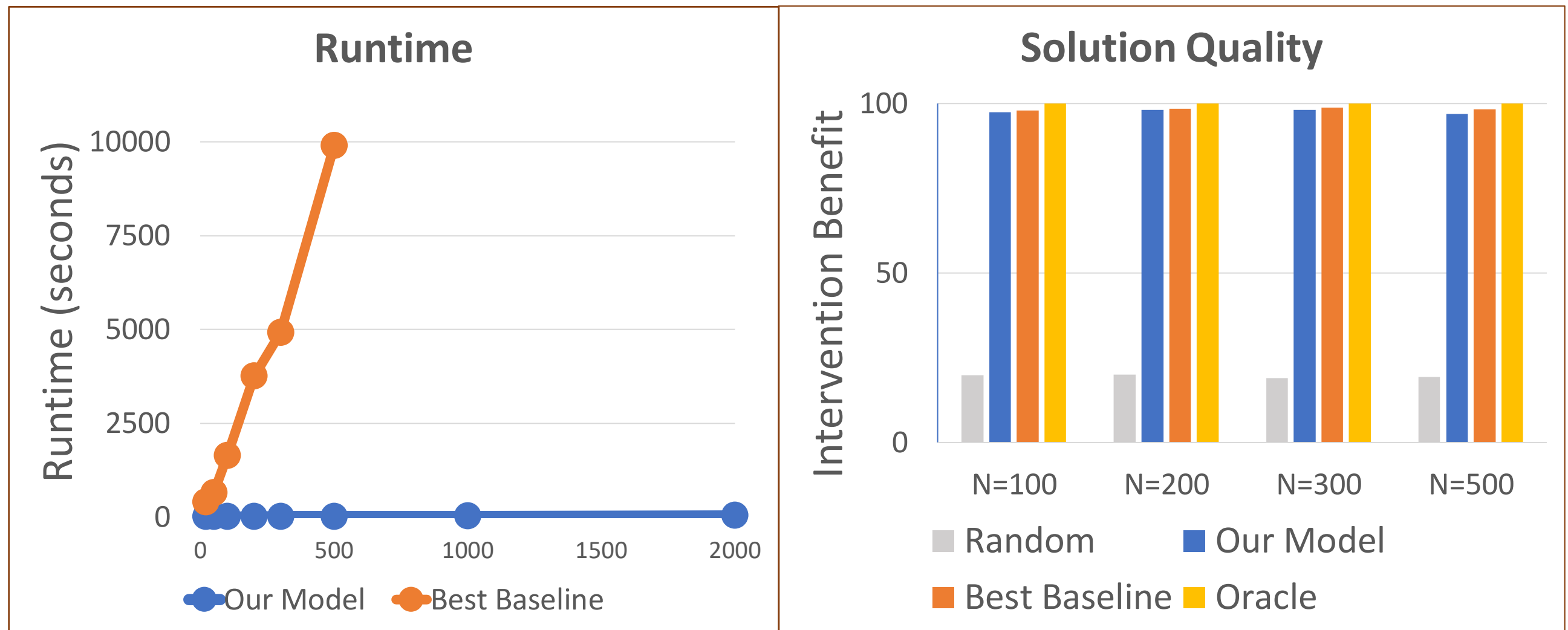


Mate



Killian

- *Orders of magnitude speedup with no solution quality loss*



How Did the Projects Get Launched

:

**Launched 6 separate
AI for Social Good Projects
Google, Academics, NGO**

Workshop at Google Research India for Matchmaking

Support from Google: Funding, Compute, Google Collaboration

Outline

Public Health



Conservation

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

Poaching of Wildlife in Uganda

Limited Intervention (Ranger) Resources to Protect Forests

Snare or Trap



Wire snares



Focus on Threat prediction

Diving up the area into 1 Km x 1 Km Grid cells



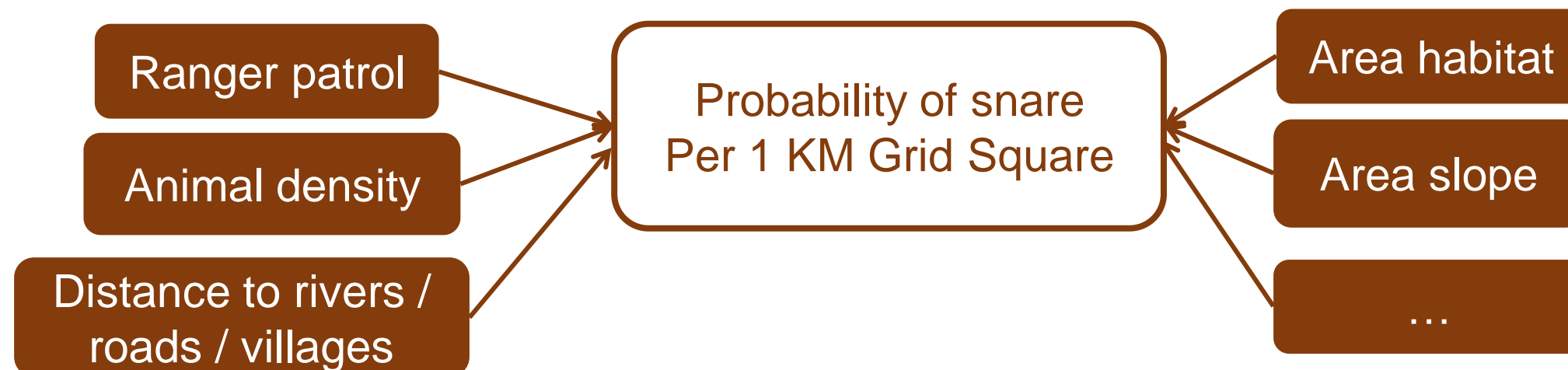
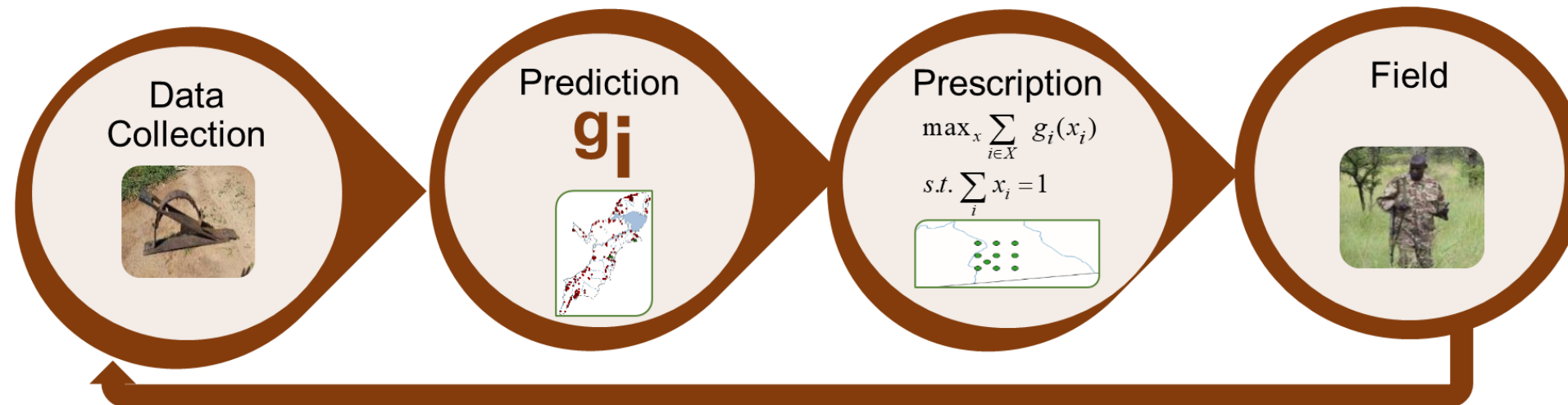
Learning Poacher Model: Uncertainty in Observations



Nguyen



Gholami

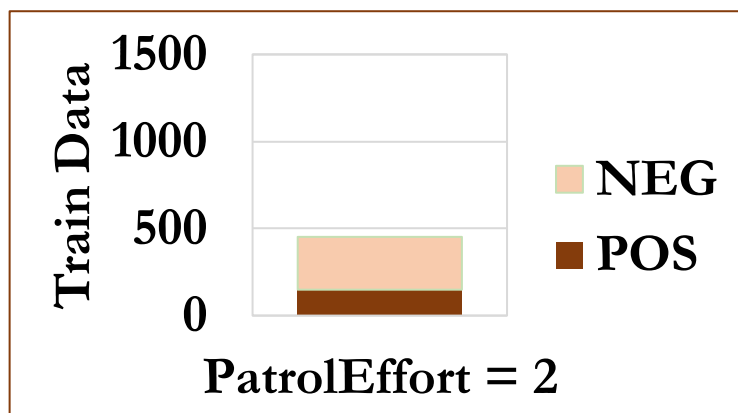
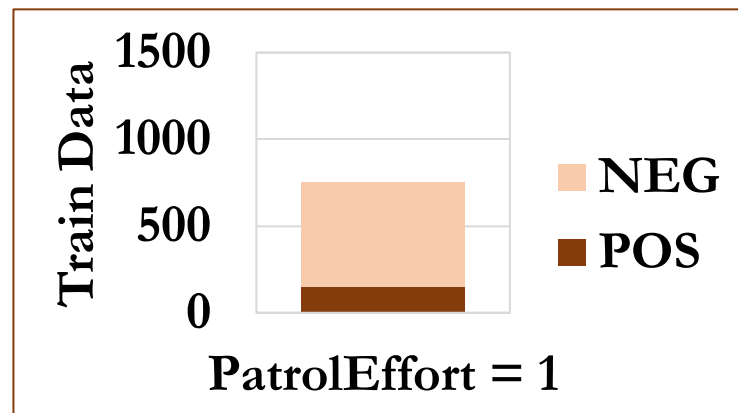
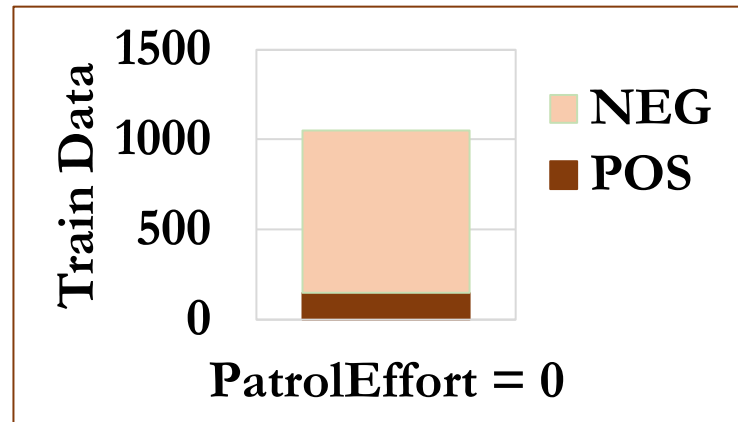


Poacher Modeling

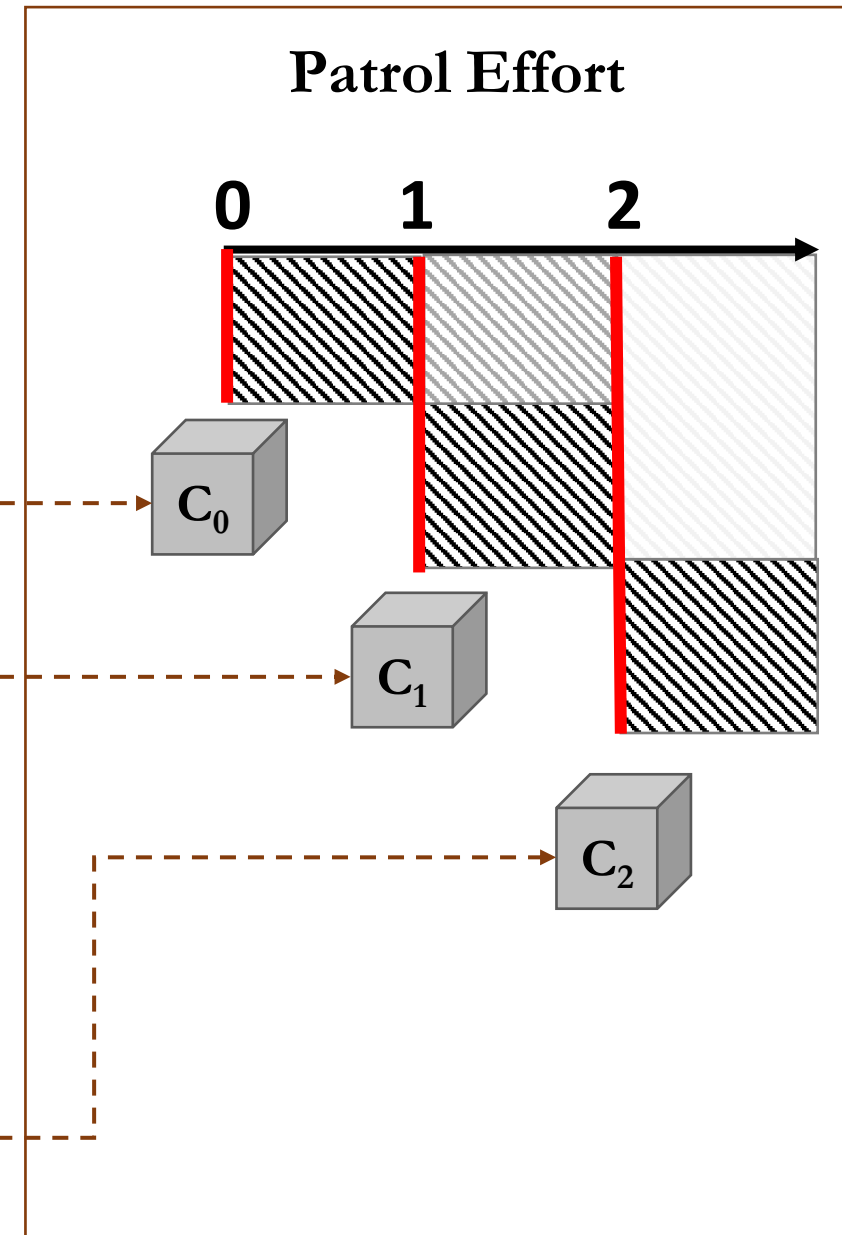
Imperfect Observation Ensemble Model



Training: Filtered Datasets



Predict: Ensemble of Classifiers



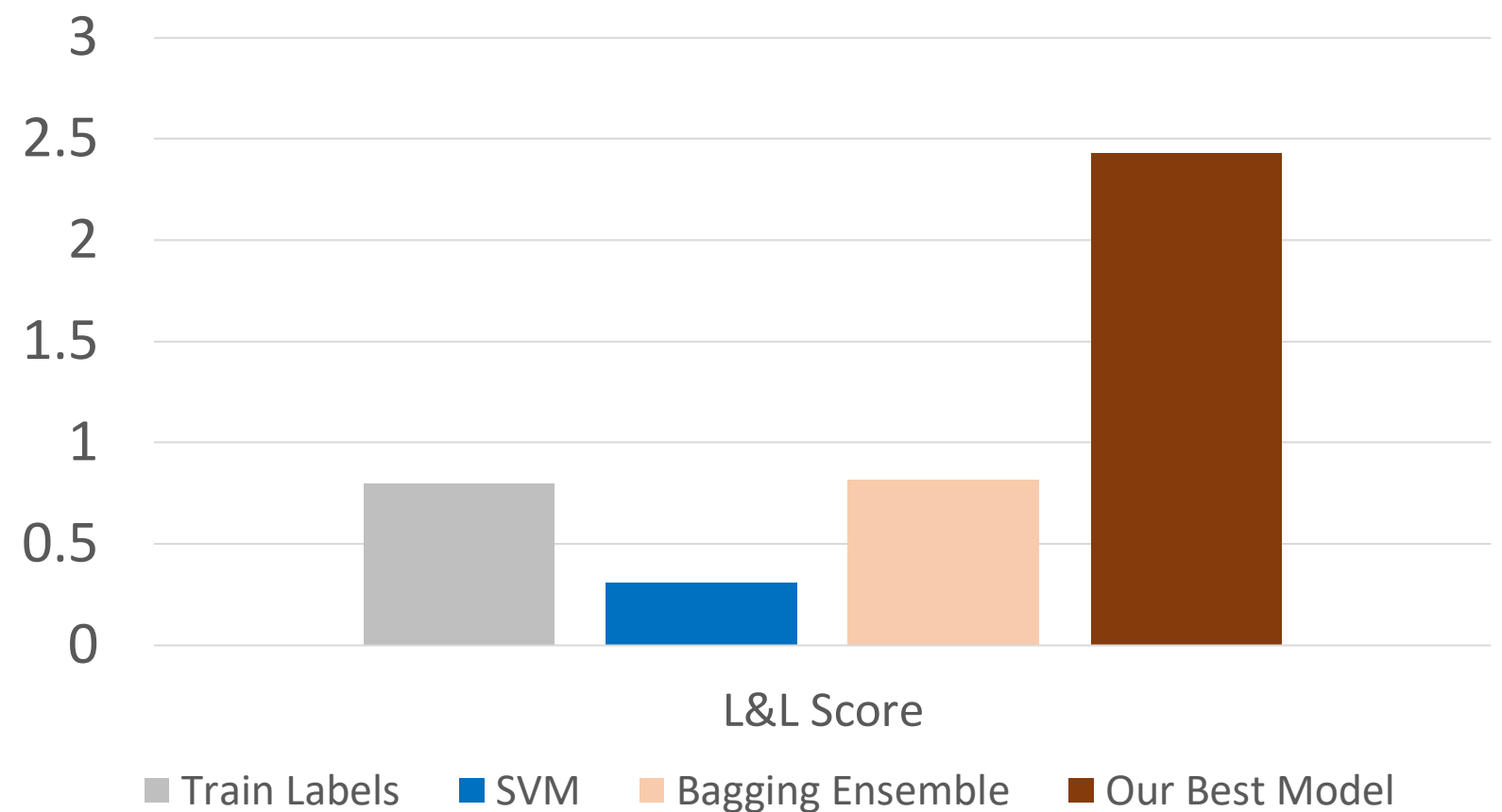
PAWS: Protection Assistant for Wildlife Security Adversary Model in the Lab



Poacher Behavior Prediction



Results from 2016



PAWS: First Pilot in the Field

(AAMAS 2017)



Ford

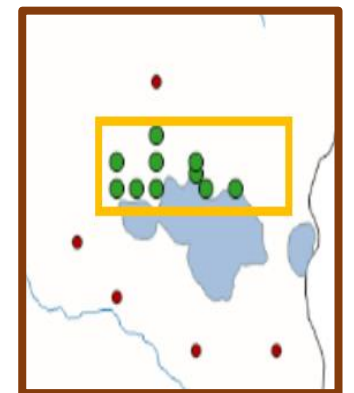
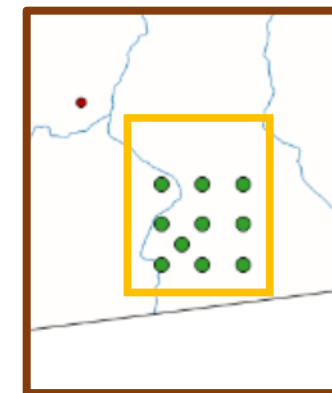
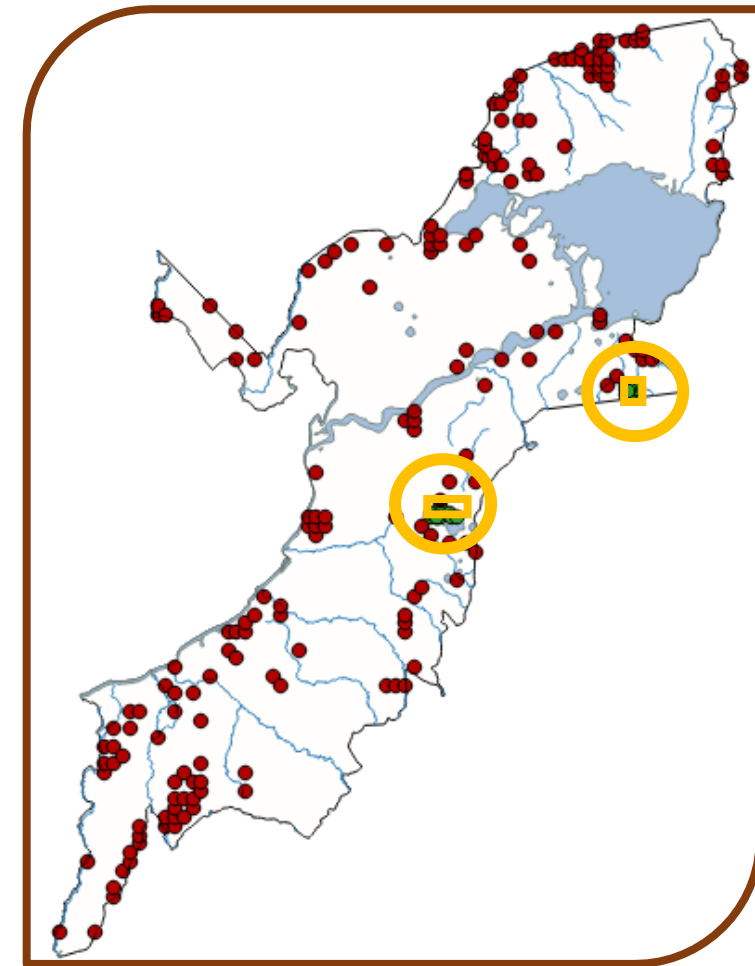


Gholami

- Two 9-sq.km areas, infrequent patrols



- Poached elephant
- 1 elephant snare roll
- 10 Antelope snares



PAWS Predicted High vs Low Risk Areas: 2 National Parks, 24 areas each, 6 months

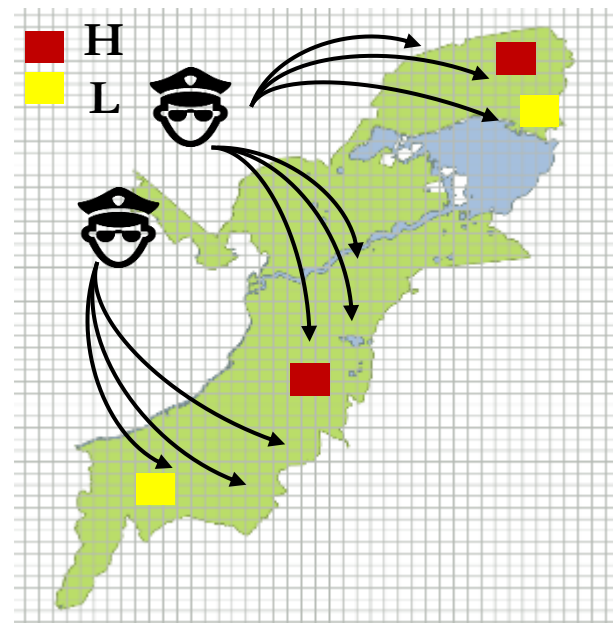
(ECML PKDD 2017, ICDE 2020)



Ford

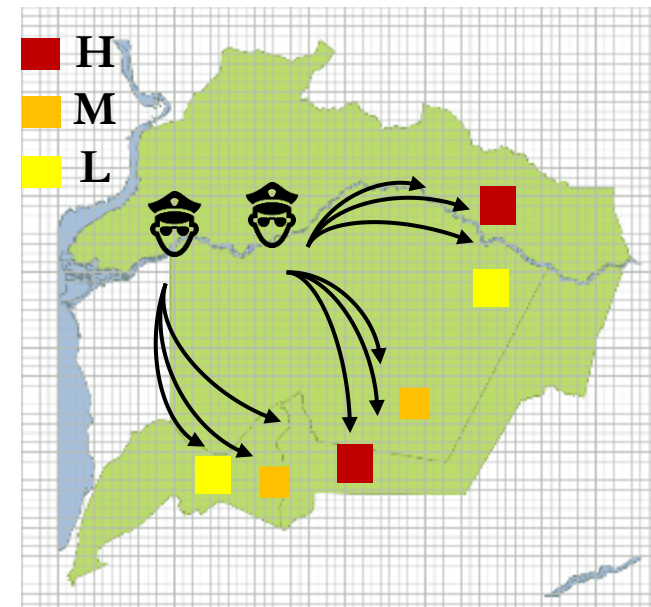
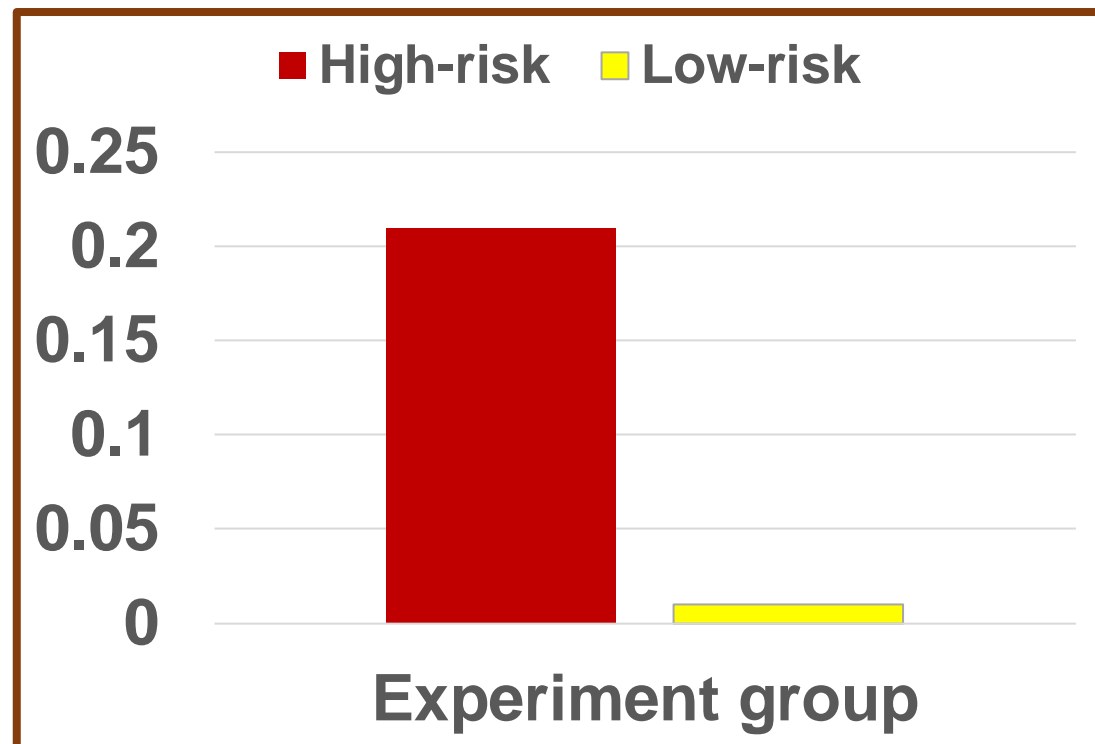


Gholami



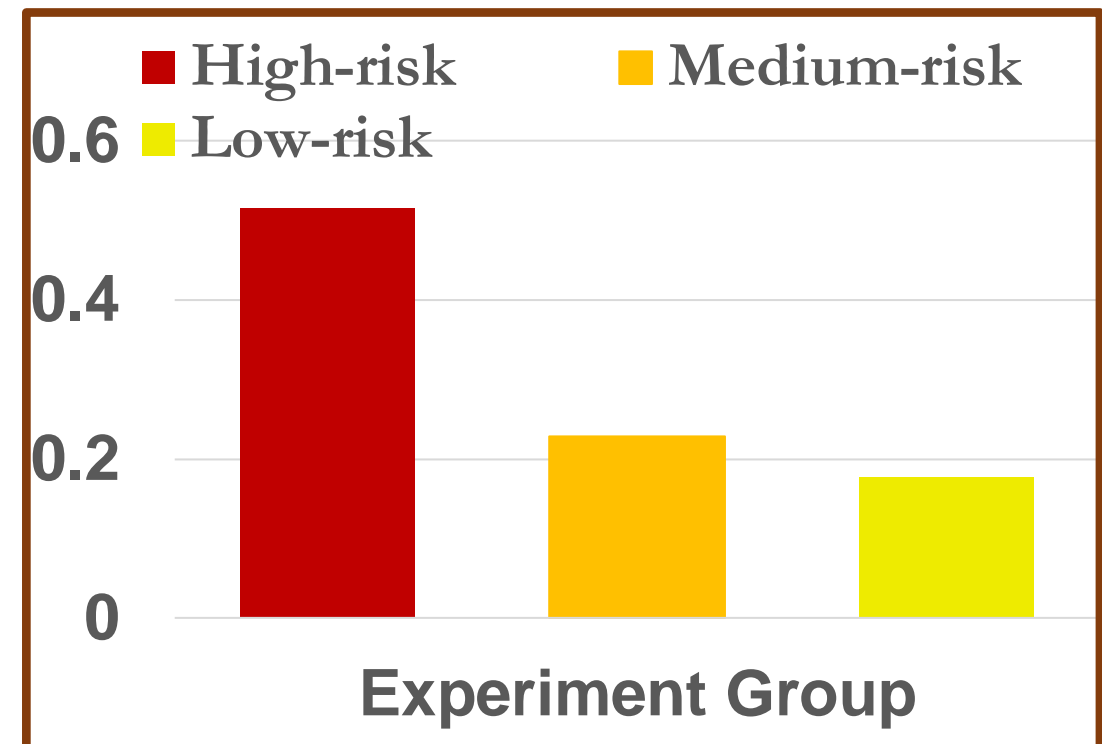
Queen Elizabeth National Park

Snares per patrolled sq. KM



Murchison Falls National Park

Snares per patrolled sq. KM



PAWS Real-world Deployment

Cambodia: Srepok Wildlife Sanctuary

(ICDE 2020)



Xu

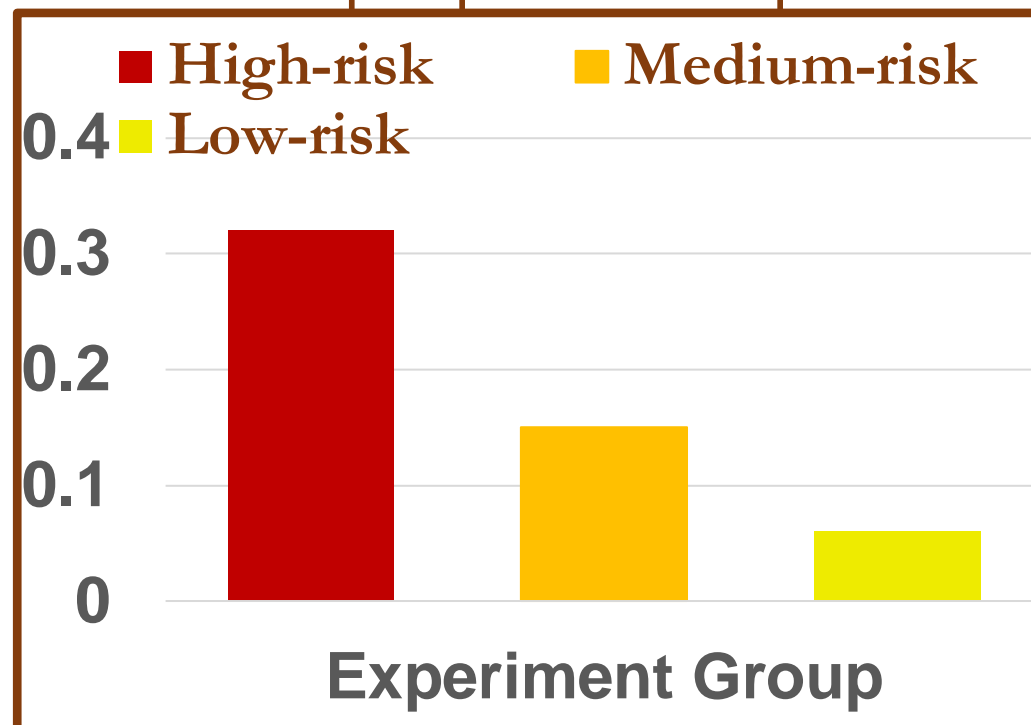


"@Milind: I am Super excited with the results. Let's get this going on other countries too this year."



Rohit Singh, WWF (2019)

Snare traps per patrolled sq. KM



■ *521 snares/month our tests*

VS

■ *101 snares/month 2018*

PAWS GOES GLOBAL with SMART platform!!



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

Also: Protect Forests, Fisheries...

How Did the Projects Get Launched

:

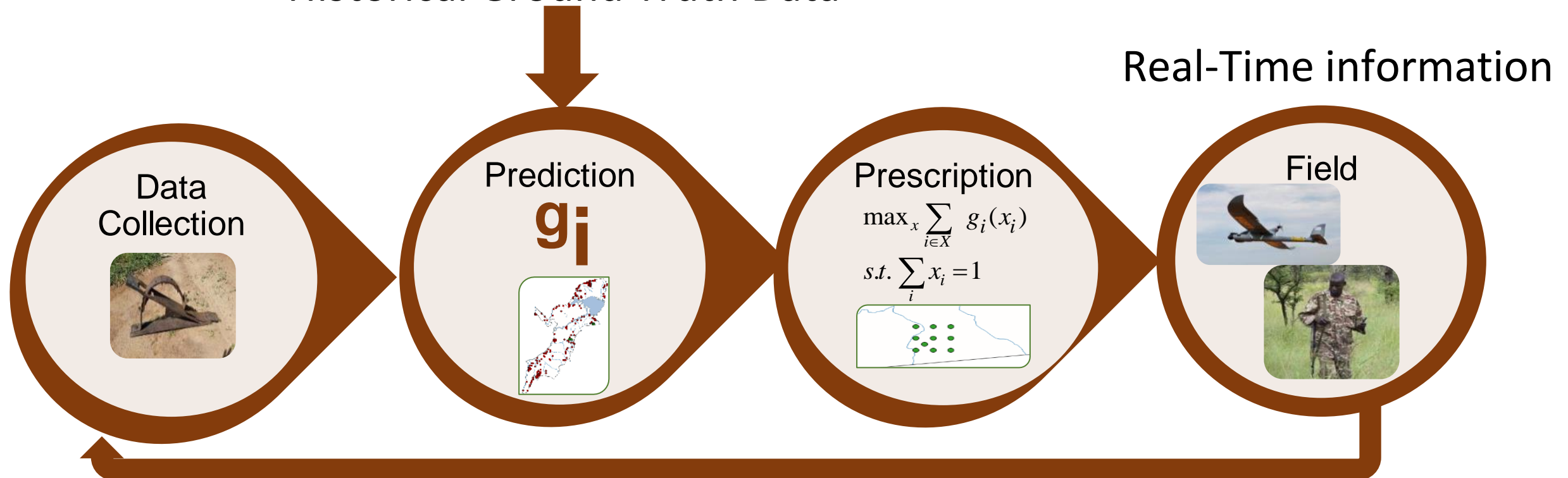
Launched PAWS project for Wildlife conservation

Met WCS officials in person in Uganda to get the project going

Support as academics: Will provide AI expertise

Green Security Games: Integrating Real-Time Information in the Pipeline

Learn predictions with
Historical Ground Truth Data

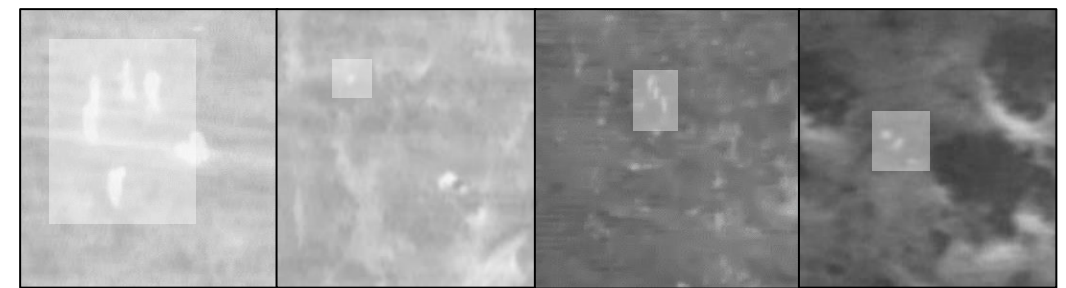
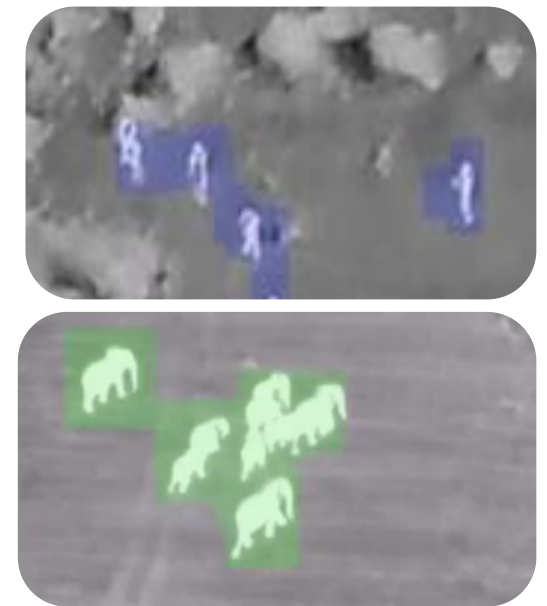
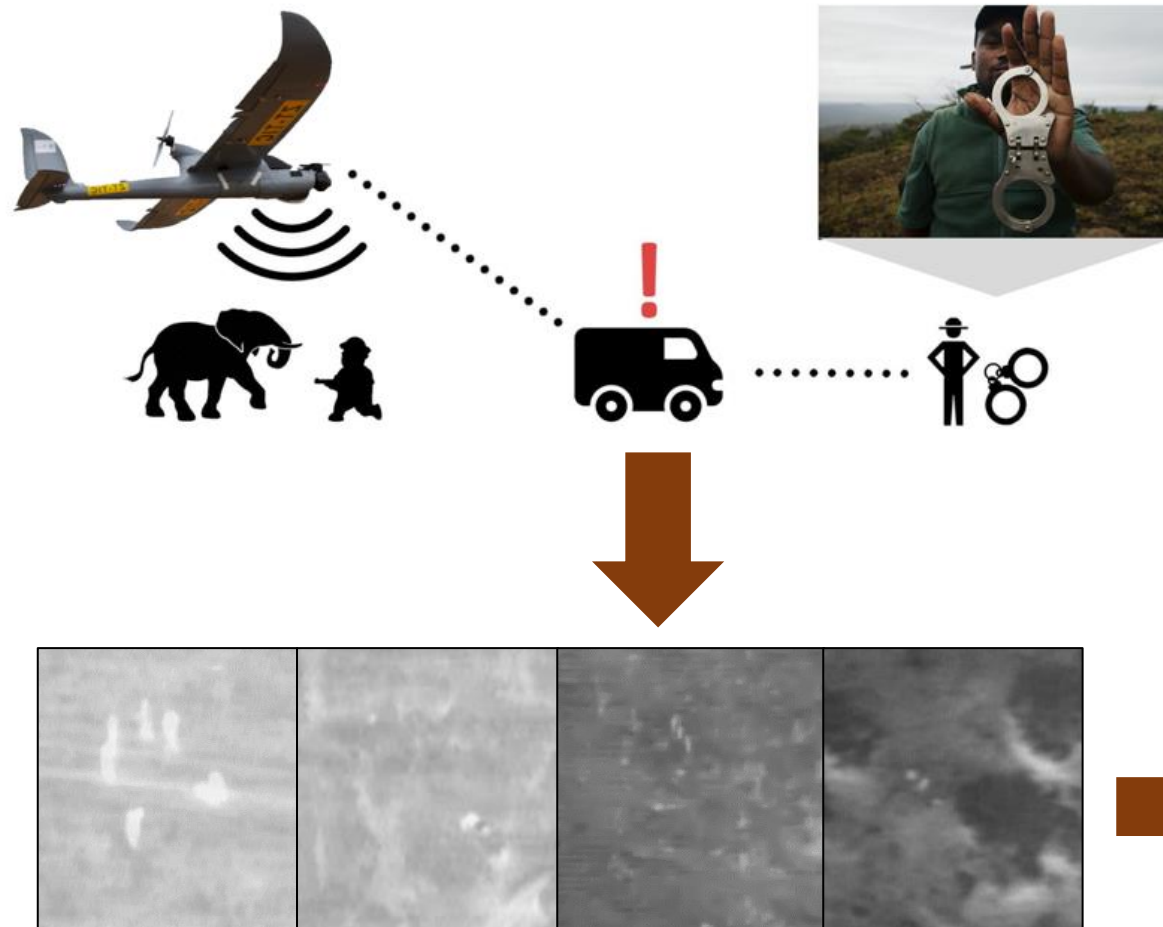


Green Security Games: Integrating Real-Time “SPOT” Information

(IAAI 2018)



Bondi



Goal: automatically find poachers

How Did the Projects Get Launched

:

Launched SPOT project for Wildlife conservation

Air Shepherd sent an email to us to collaborate

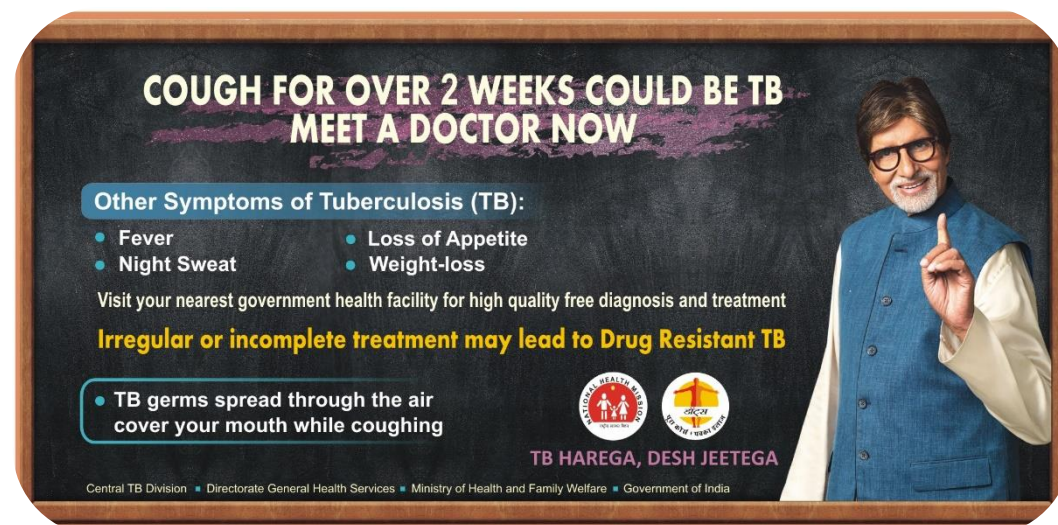
Support as academics: Will provide AI expertise

Three Key Takeaways

What are key problem types for AI for Social Good in public health & conservation?

What are some key AI research challenges (pay attention to models, not details)

How do we launch projects in AI for Social Good?



Future: AI Research for Social Impact



It is possible to simultaneously advance AI research & achieve social impact



Data to deployment perspective: Not just improving algorithms



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



AI for Social Impact should be evaluated differently

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