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

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AI & Multiagent Systems Research for Social Impact

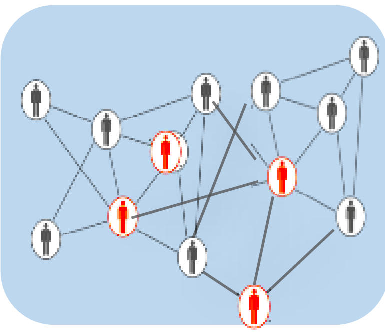
Public Health

Conservation

Public Safety and Security

Optimize Our Limited Intervention Resources

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



Social Networks & Bandits

Public Health


Green security games

Conservation


Public Safety & Security

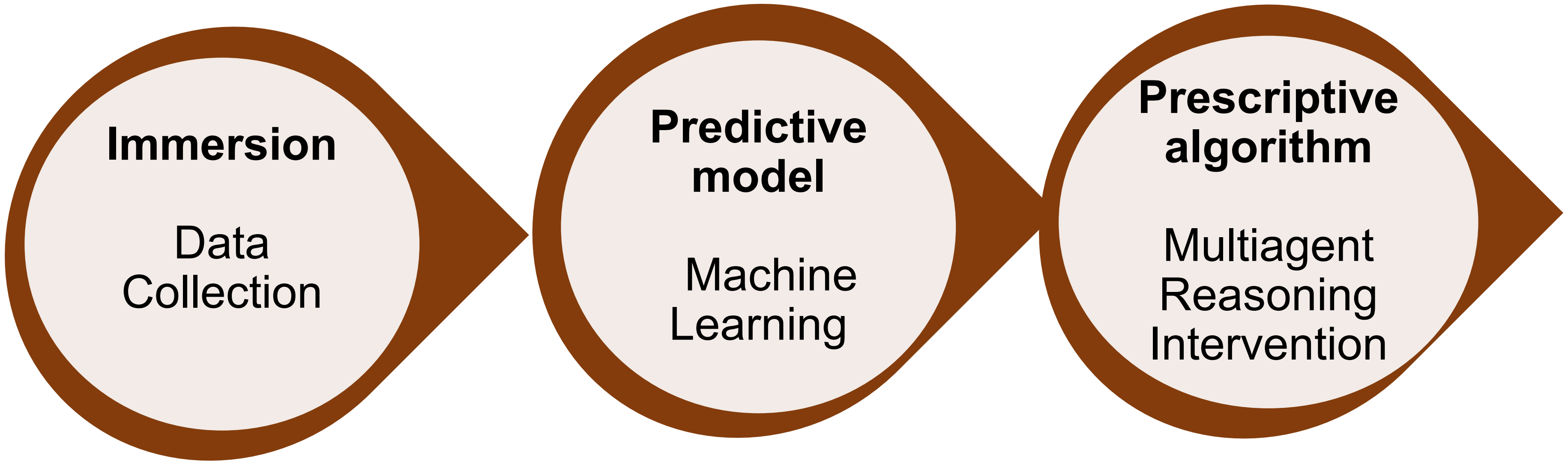
Stackelberg security games

Lesson #2:

Partnerships with NGOs (non-profits) & Govt organization crucial

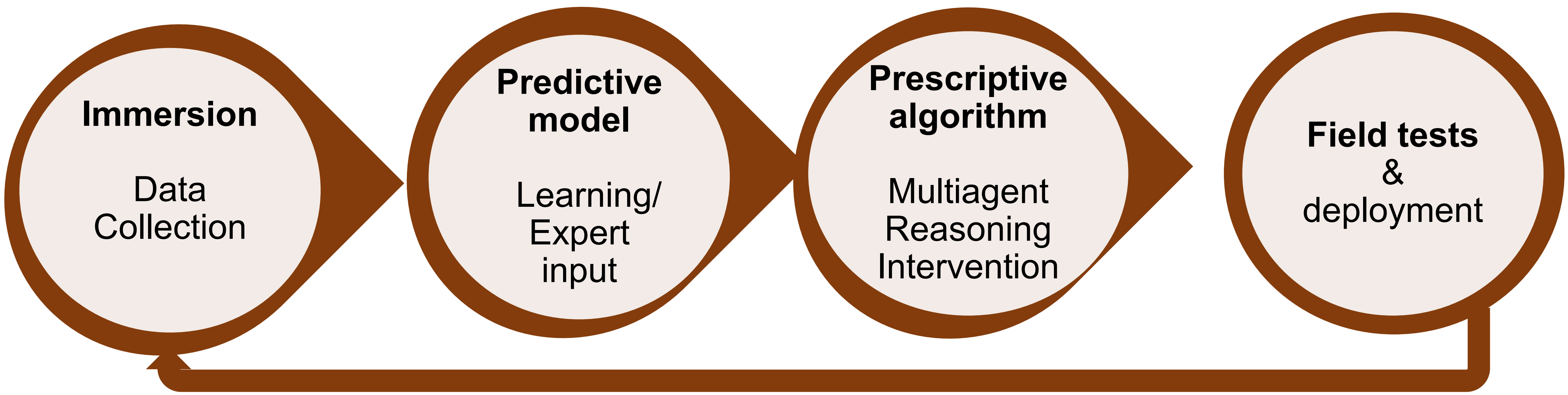
Empower non-profits to use AI tools; avoid being gatekeepers to AI4SI technology

Lesson #3:
Data-to-deployment pipeline; not just improving algorithms



Lesson #3:
Data-to-deployment pipeline; not just improving algorithms

Field test & deployment: Social impact is a key objective



Outline

Public Health

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

Conservation

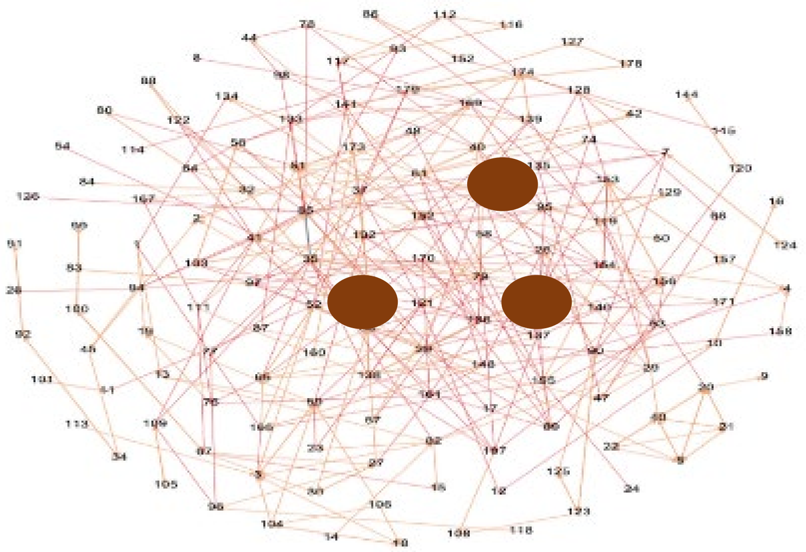
- Cover papers from 2017-now [AAMAS, AAAI, IJCAI, NeurIPS…]
- PhD students & postdocs highlighted

Information dissemination & behavior change
Optimizing Limited Intervention (Social Worker) Resources

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*

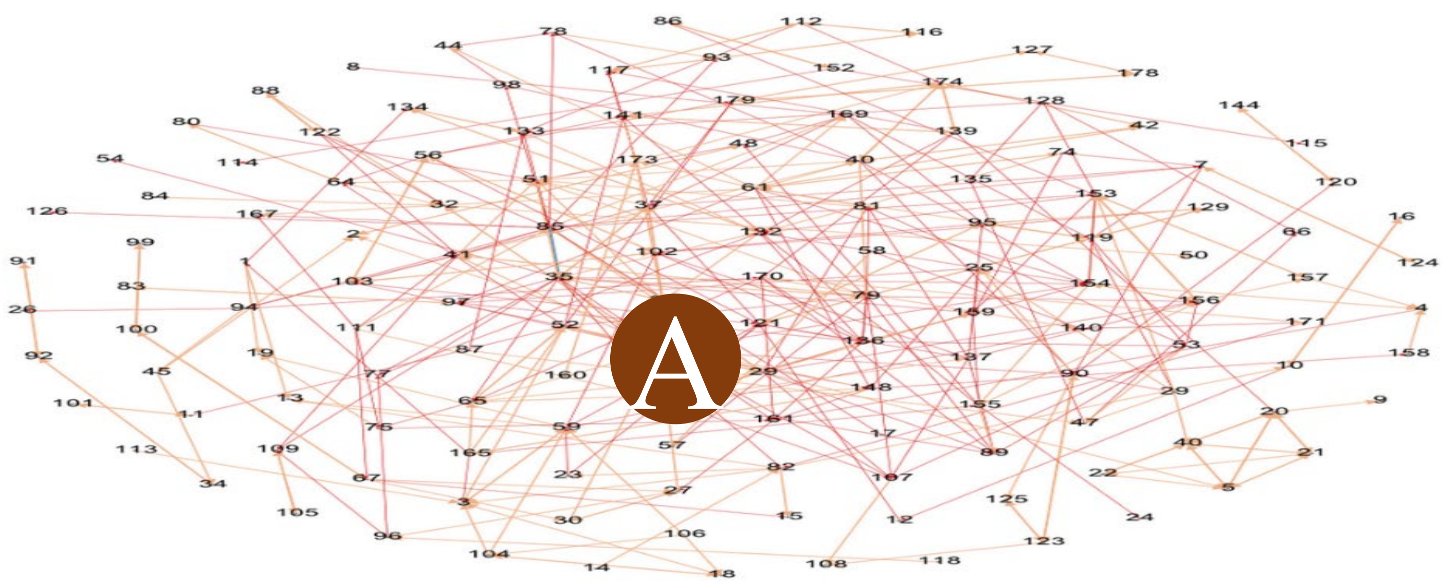
Influence Maximization in Social Networks



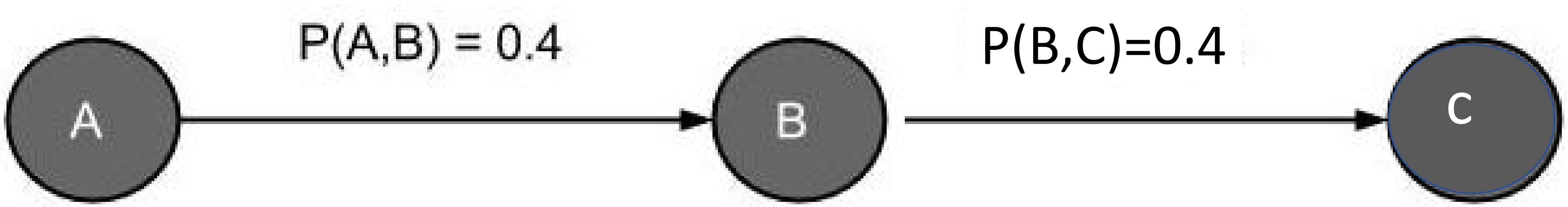
- Given:
  - Social network Graph G
  - Choose K “peer leader” nodes
  - Assume: Independent cascade model of information spread

- Objective:
  - Maximize expected number of influenced nodes

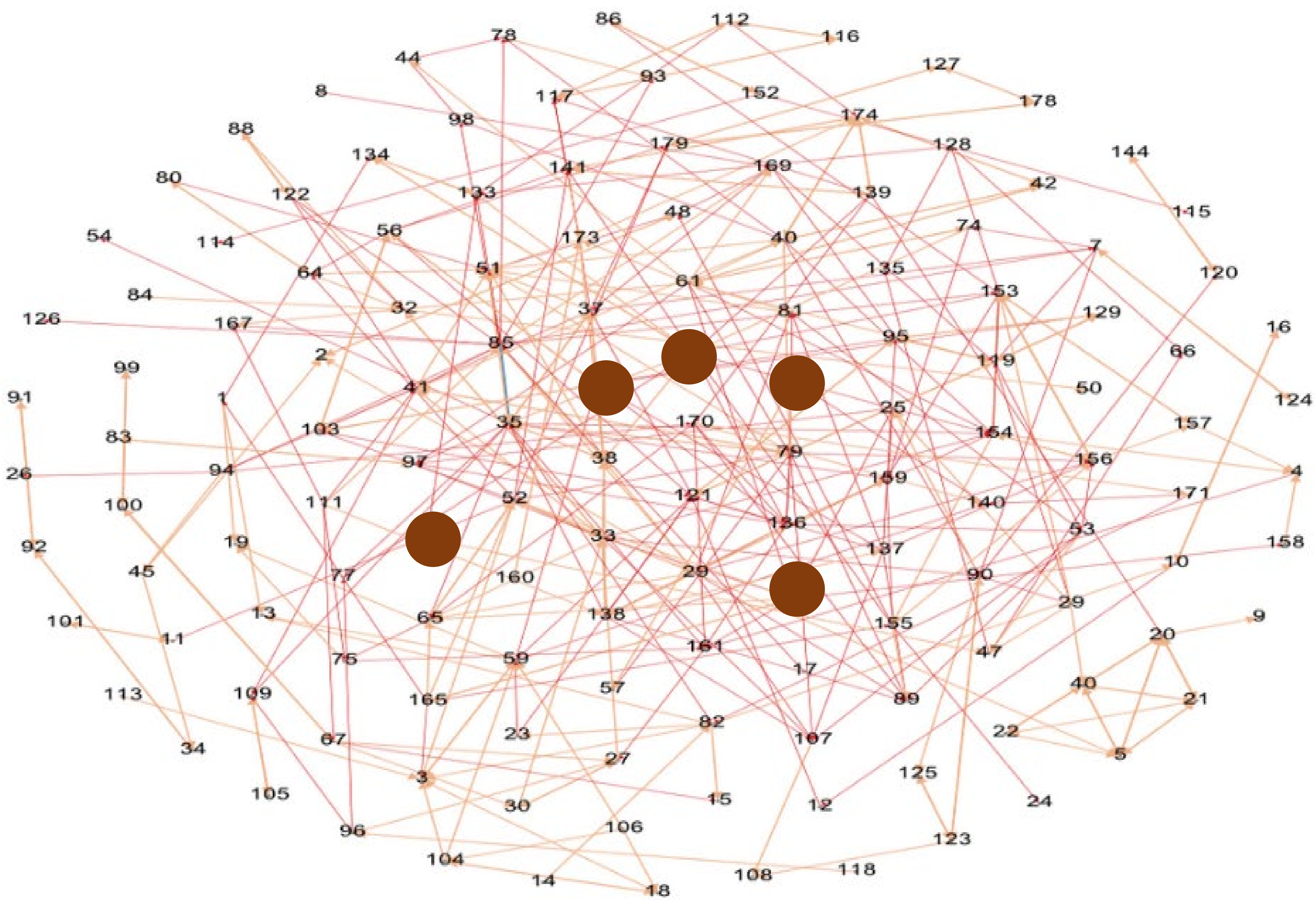
Independent Cascade Model



- Propagation Probability (for each edge)



Influence Maximization (Budget = 5 nodes)




PEER LEADERS
OUR MISSION
SEXUAL HEALTH
HIV 101
COMMUNICATION
LEADERSHIP
SELF-CARE
Facts
HIV is a virus
Getting HIV from
EMPIRE
STATE
718
NYC

Influence Maximization in Social Networks
Three Key Challenges Combined Together

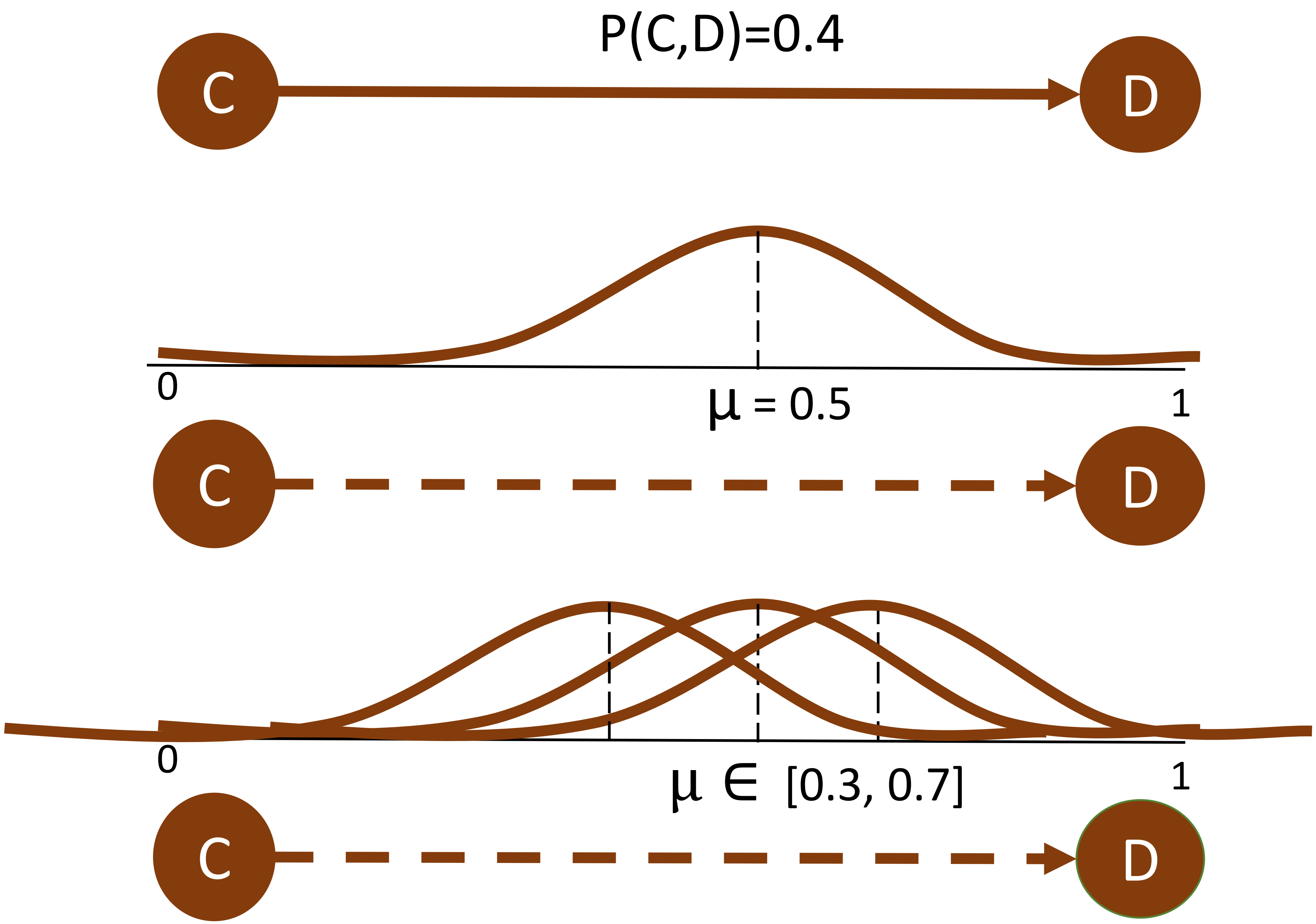
Research challenges in AI for social good?

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

Sketch some ways we solve these problems

Challenge 1: Uncertainty in Real-world Physical Social Networks



Robust Influence Maximization

(AAMAS 2017)

Wilder

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

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

Algorithm

Choose Peer Leaders p ∈ P generating mixed strategy "$x \in \Delta^{|P|}$"

vs

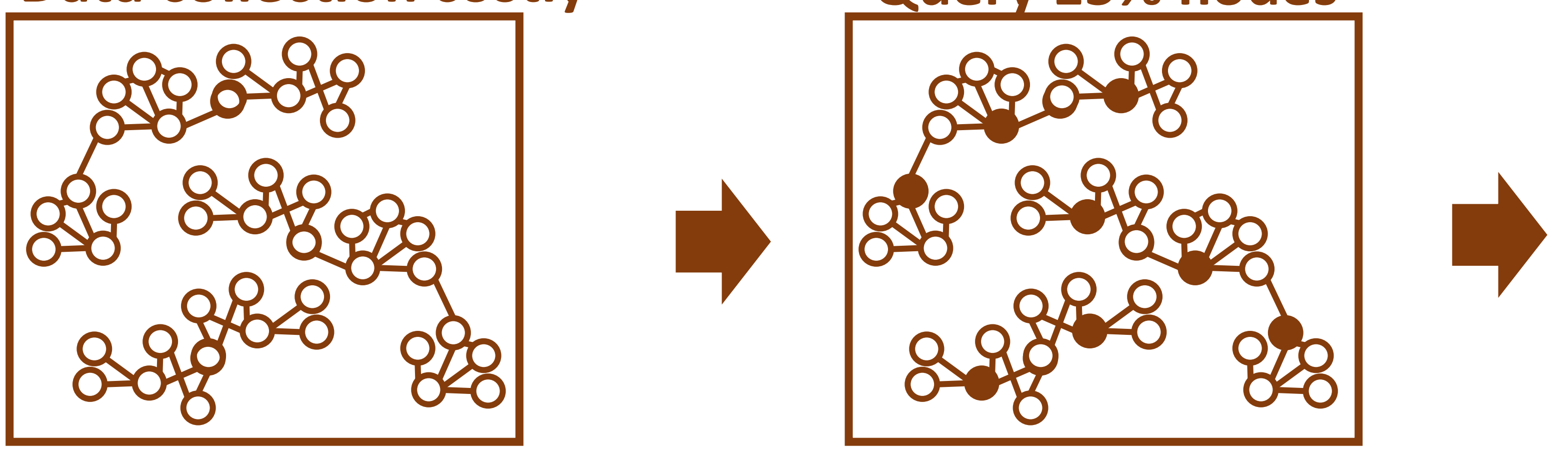
Nature

Chooses parameters

μ,σ

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

Wilder



Sampling Algorithm

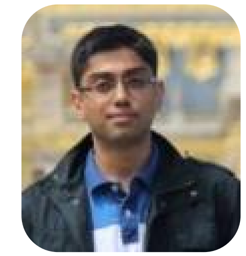
Sample node randomly & estimate size of its community;
Choose seeds from largest K communities

- 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

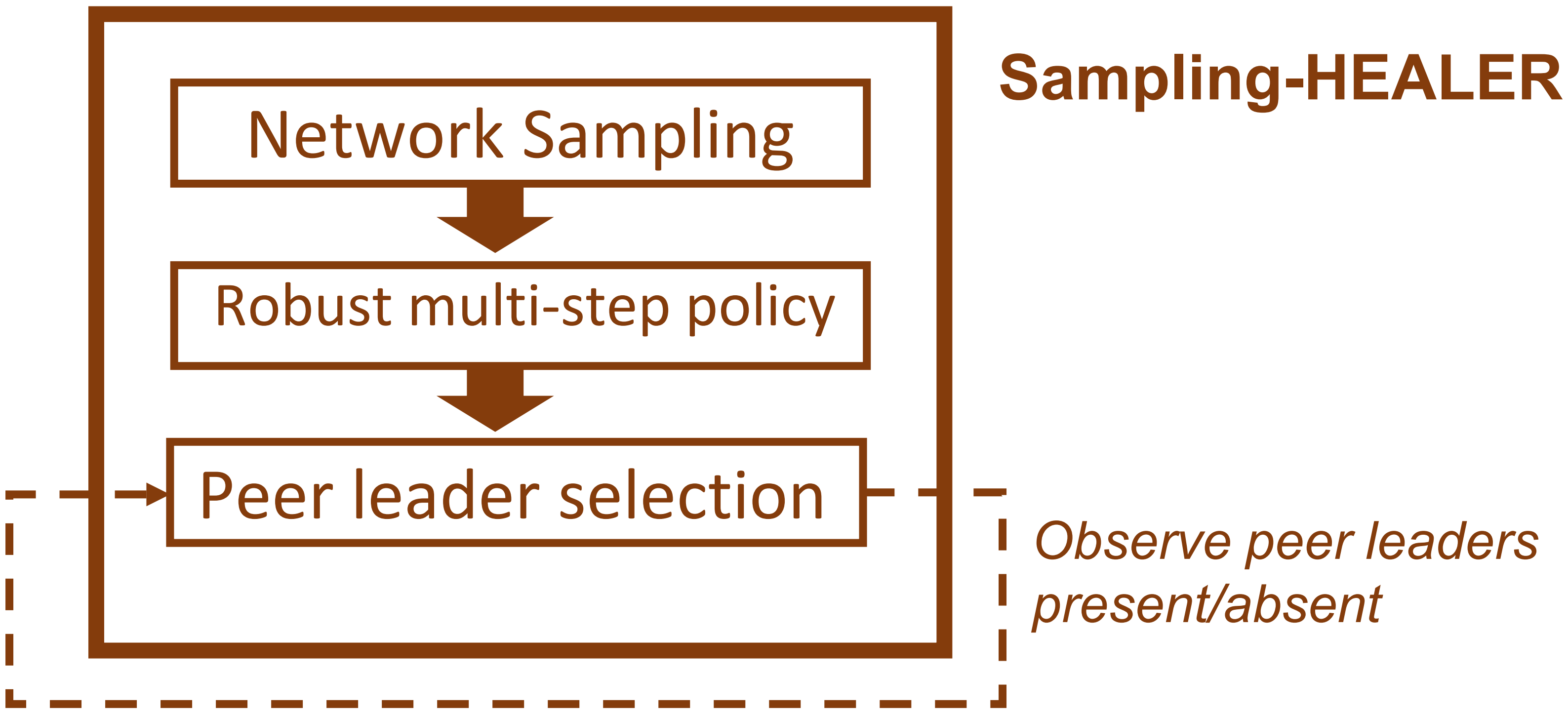
(*)Community structured: drawn from a stochastic block model

“Sampling-HEALER”
Pilot tests with Homeless Youth

(IJCAI 2018)


Yadav


Wilder




12 peer leaders

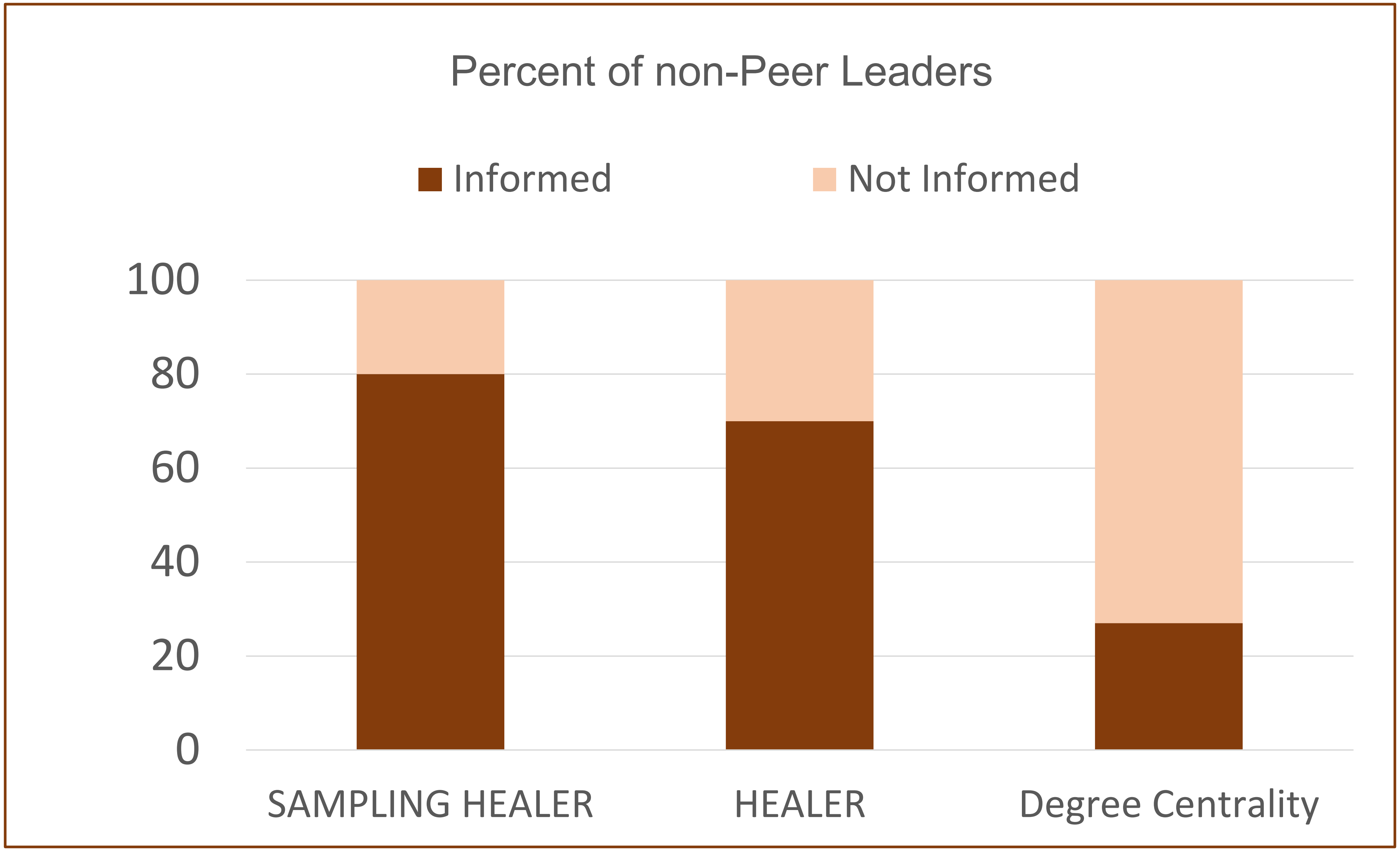
Sampling HEALER (Sampled Network)	HEALER (Full Network)	DEGREE CENTRALITY (Full Network)
60 youth	62 youth	55 youth

Results: Pilot Studies

(Journal of Society of Social Work & Research 2018)

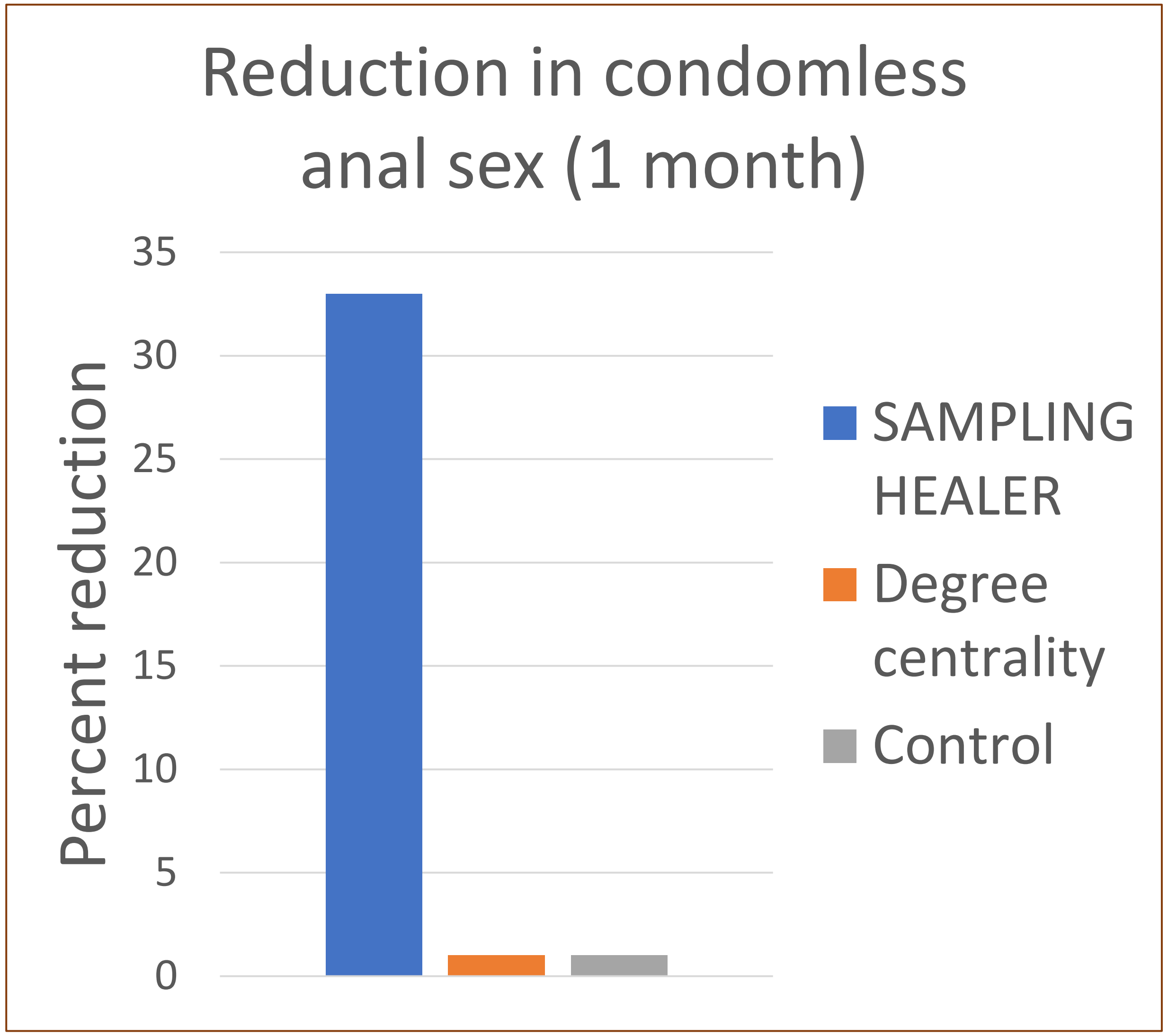
Yadav

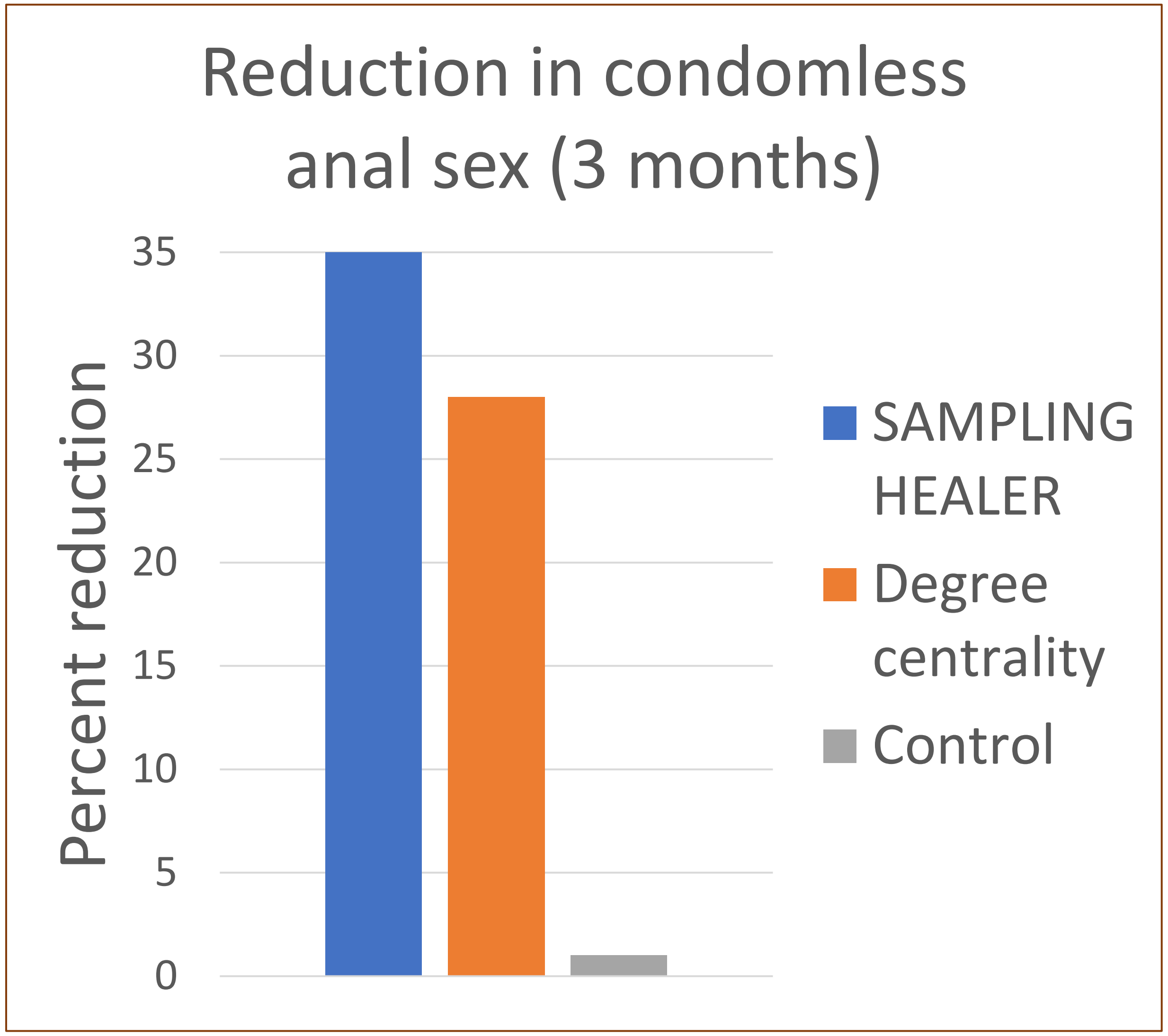
Wilder



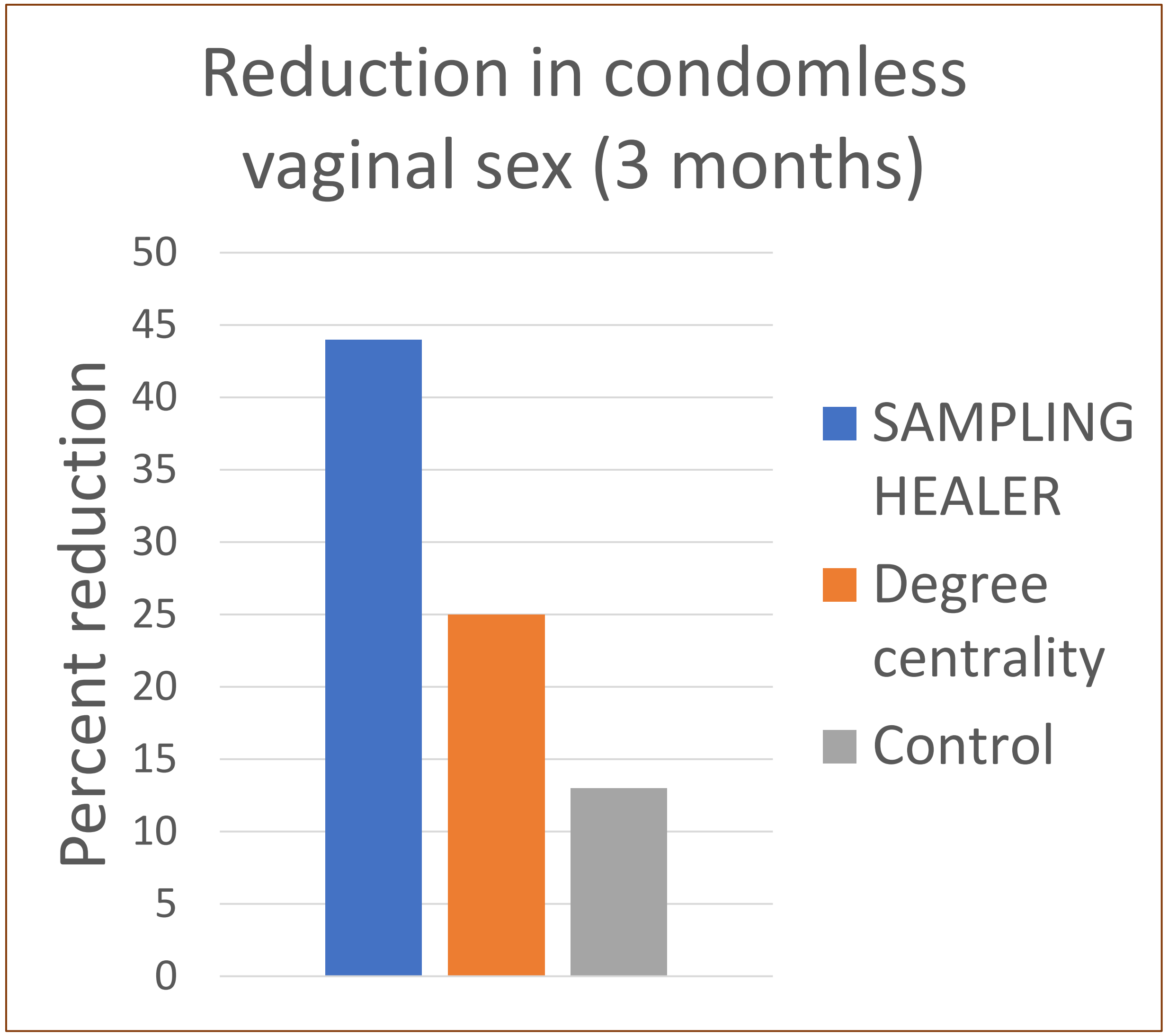
Results of 750 Youth Study [with Prof. Eric Rice]
Actual Change in Behavior?
(AAAI 2021)

First large-scale application of influence maximization for public health





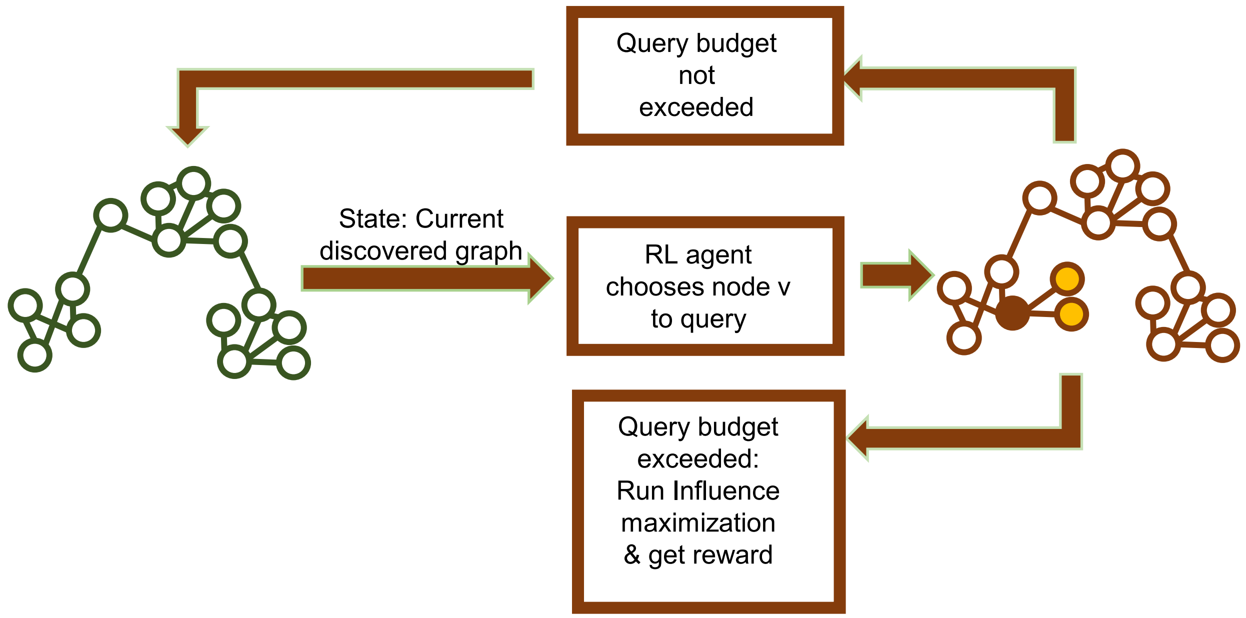
Results of 750 Youth Study [with Prof. Eric Rice]



What our collaborators are saying:

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

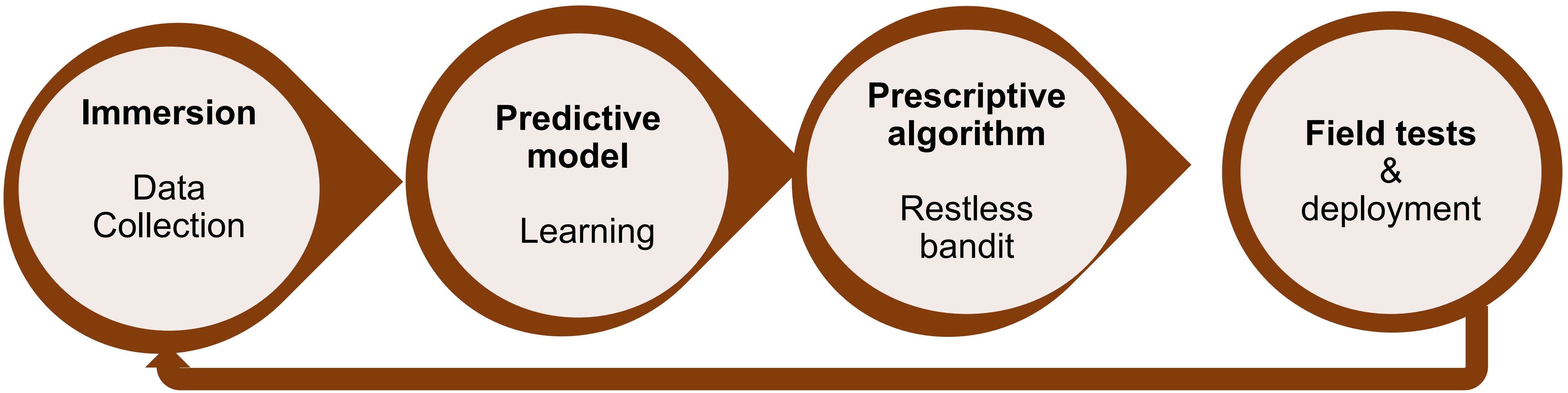
Outline

Public Health

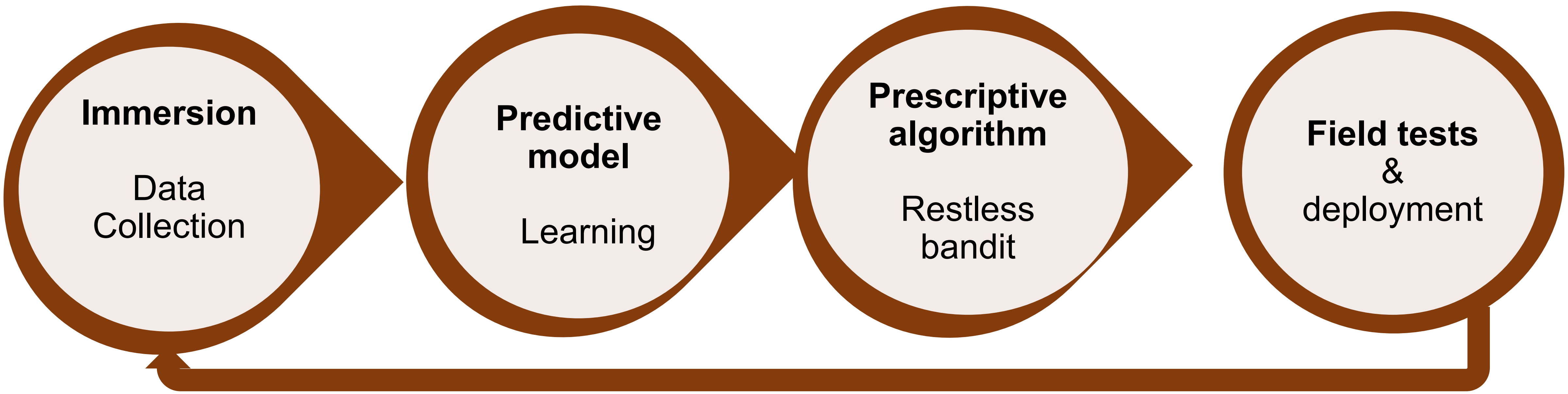
- *Health information dissemination: Social networks*
- *Health program adherence: ML & Bandits*
- *COVID-19: Agent-based modeling*

Conservation

Intervention Reasoning: Active Adherence Monitoring



Intervention Reasoning: Active Adherence Monitoring



Health Program Adherence
Maternal & Child Care in India

(IJCAI 2021)

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

armman

(Advancing Reduction in Mortality and Morbidity of Mothers, Children and Neonates)

Delivering India's Future

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*

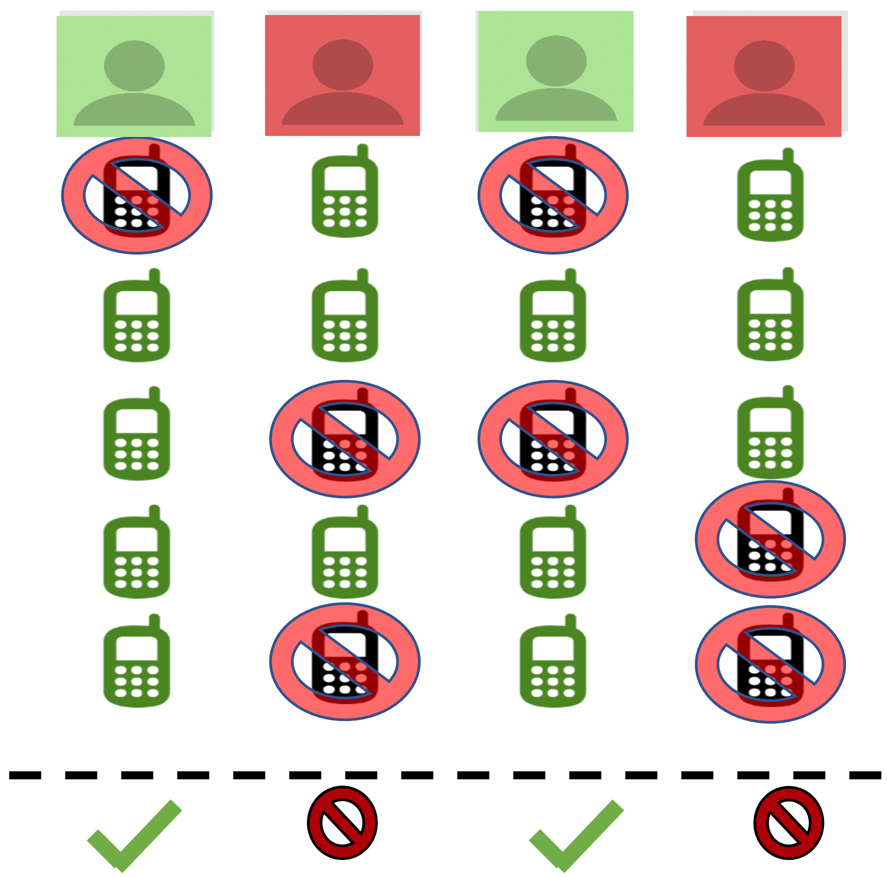
Passive Adherence Monitoring Maternal & Child Care in India

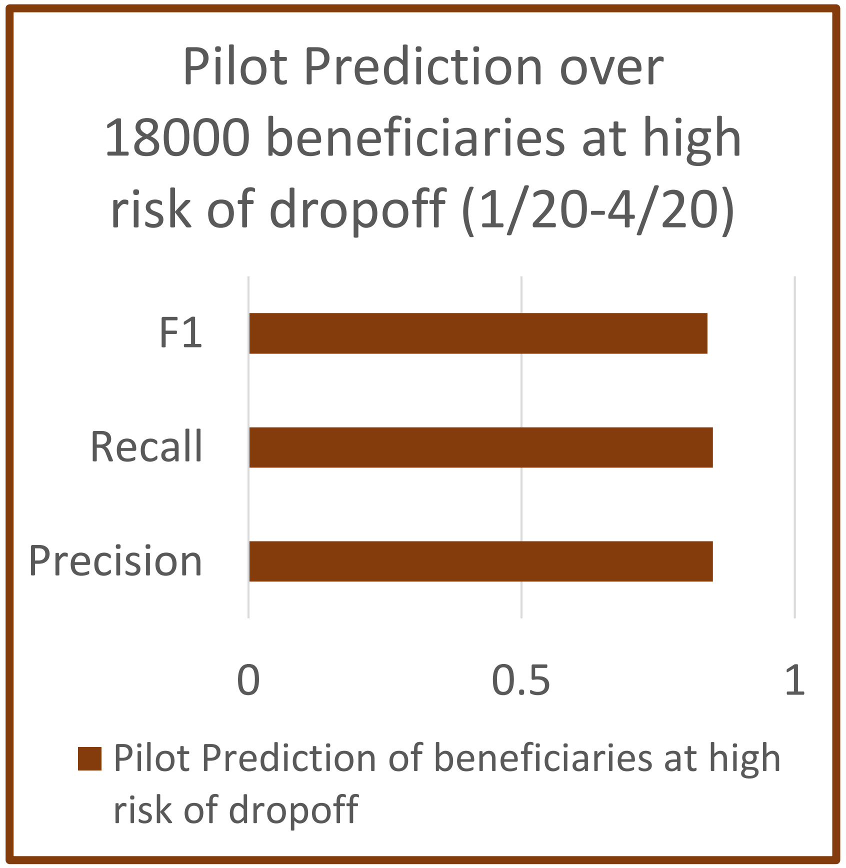
(with B Ravindran IIT Madras)

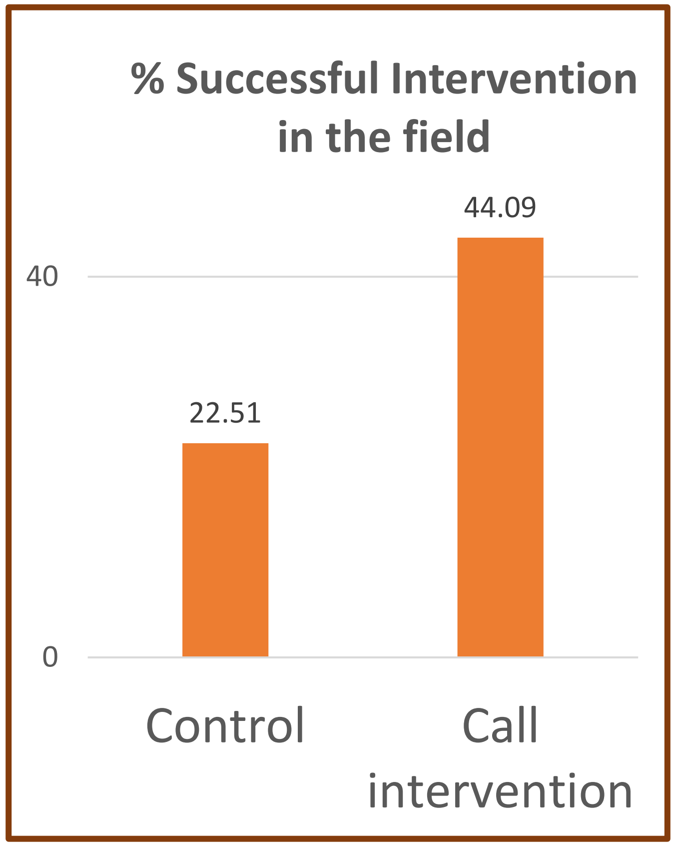
Classifier to predict beneficiaries drop out? So ARMMAN can focus interventions

- *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***

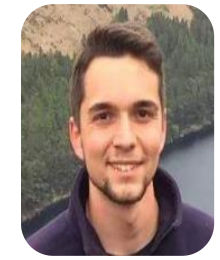






Passive Adherence Monitoring Preventing Tuberculosis in India

(KDD 2019)



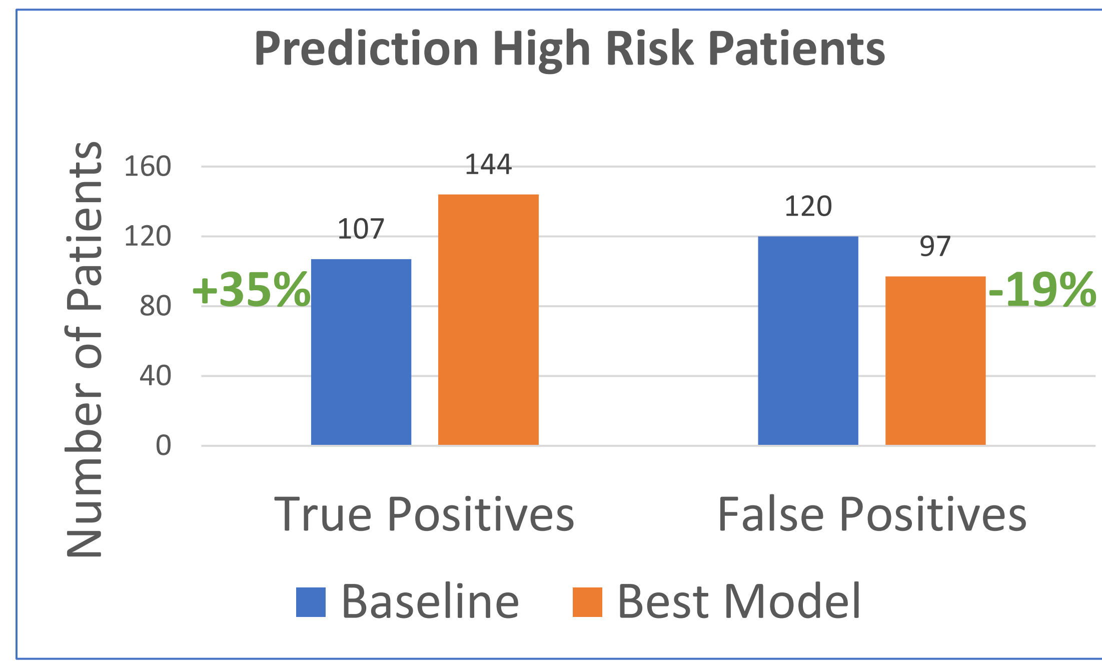
Killian

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

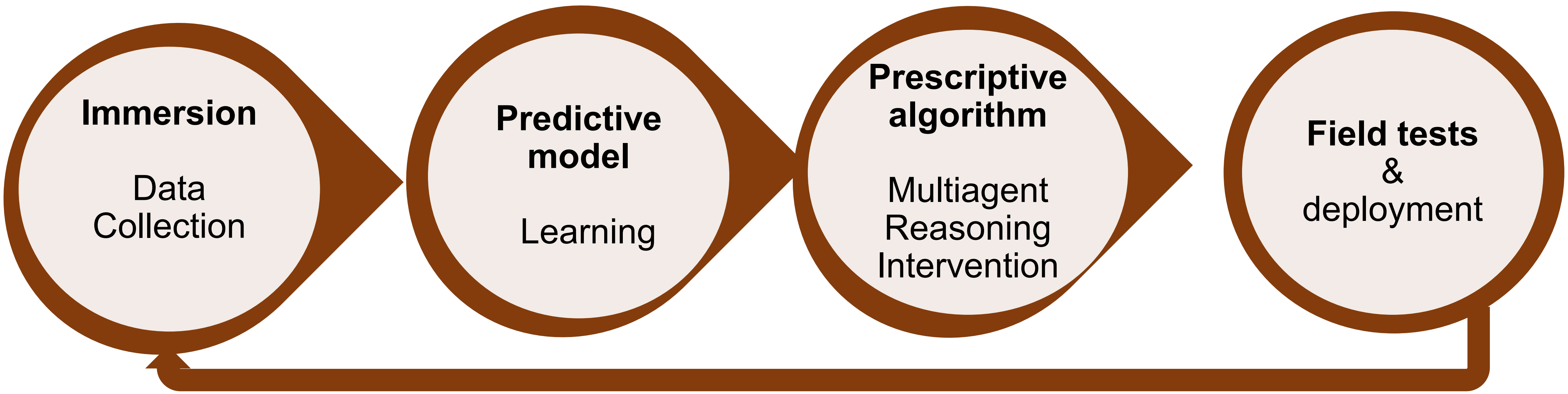
Track adherence
via daily phone calls



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

everwell

Intervention Reasoning: Active Adherence Monitoring



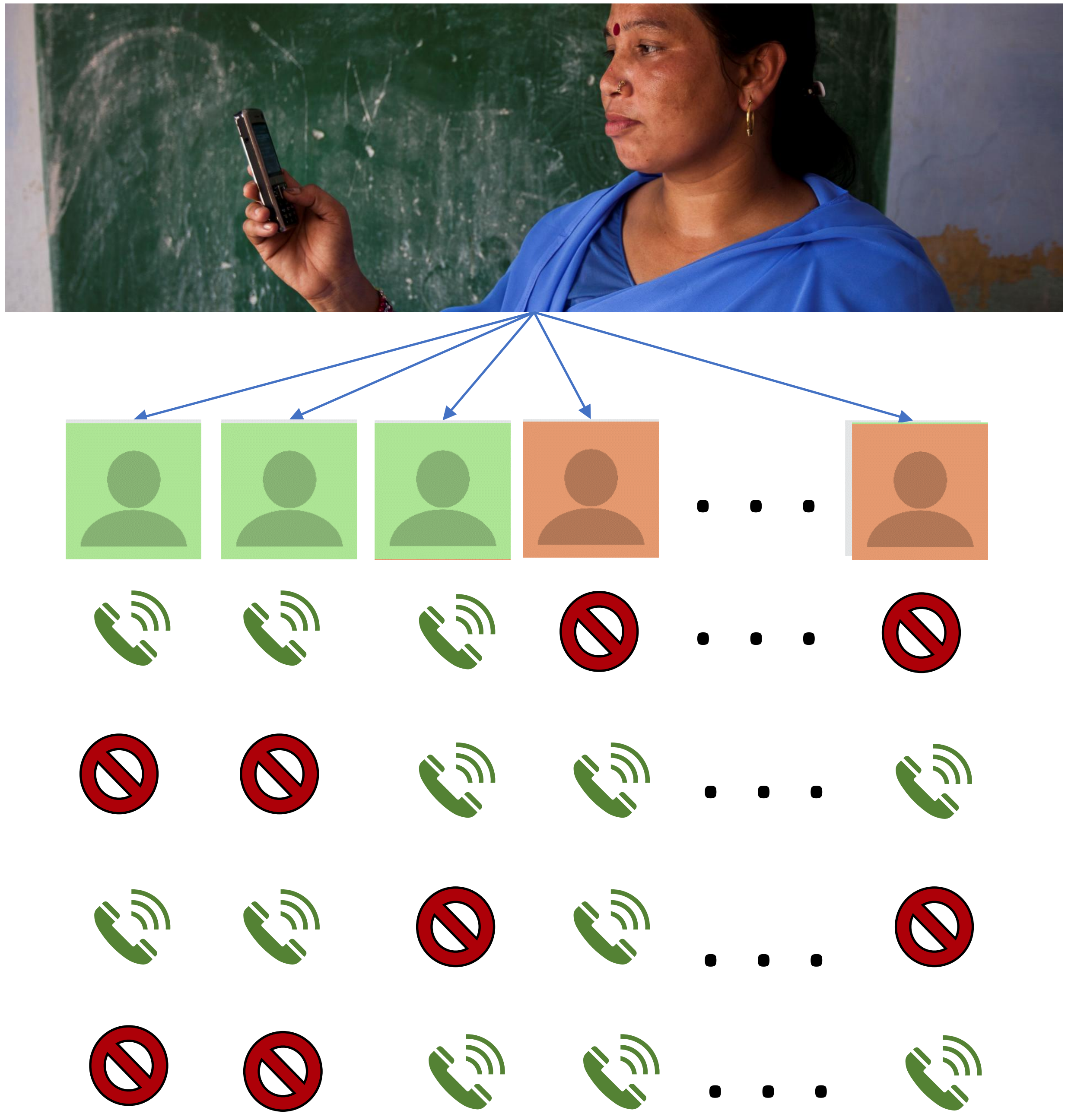
Intervention Scheduling with Scarce Data: Active Adherence Monitoring

(NeurIPS 2020)

Mate Killian

Challenge:

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



Approach: "Restless bandit"

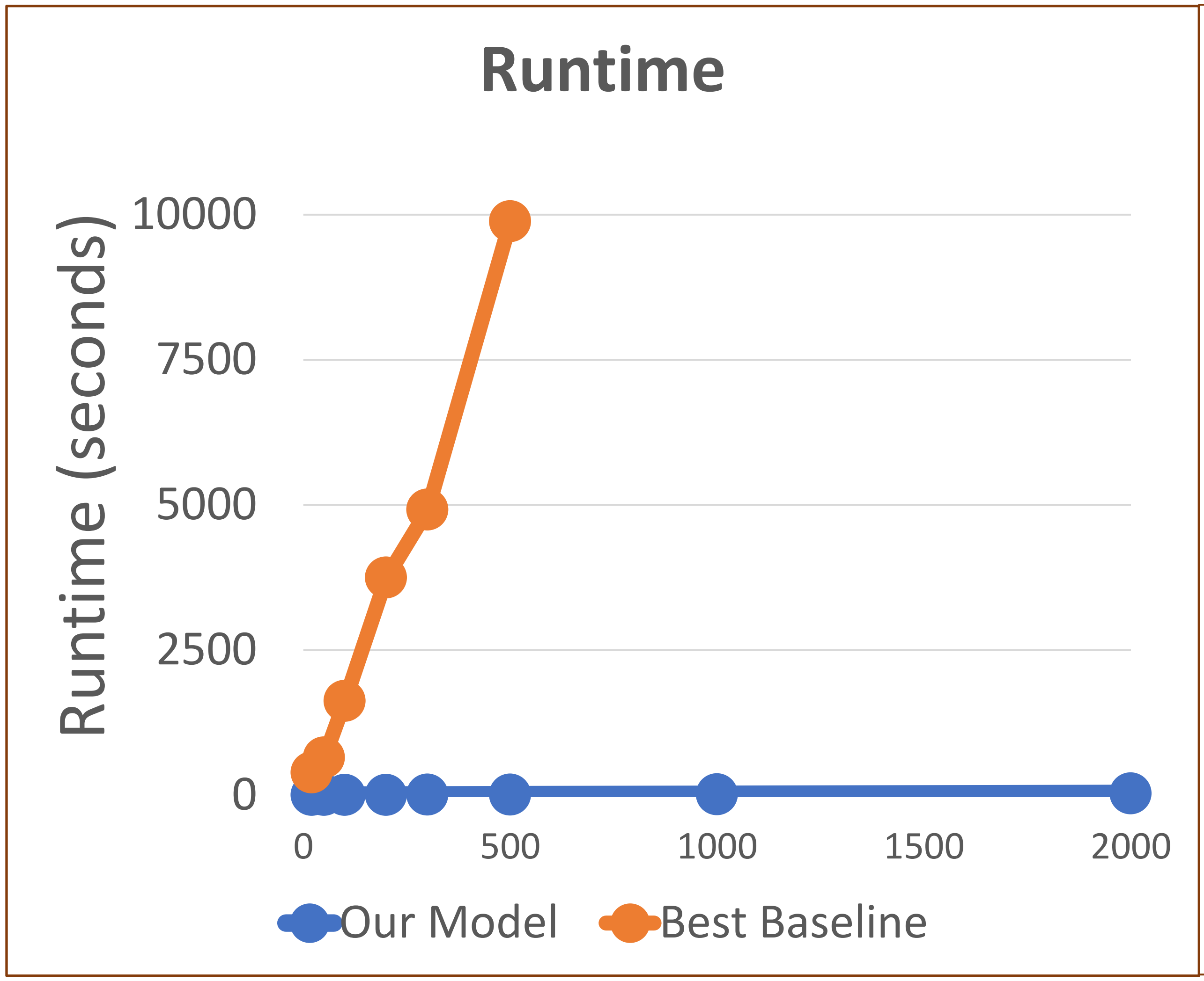
- *Each arm (patient) latent state {0, 1}*
- *0= not-adhering; 1= adhering*

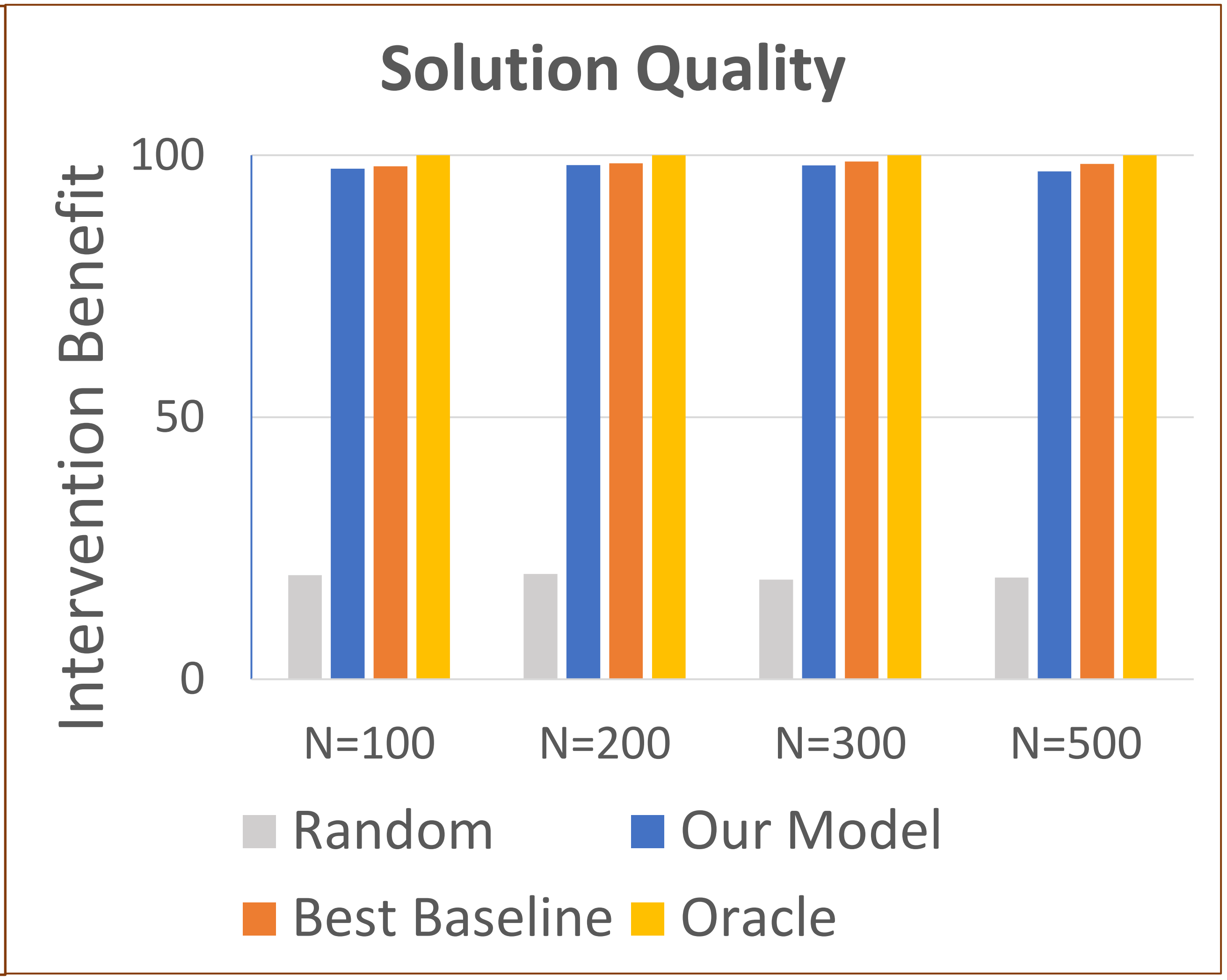
Goal: Policy for K patients to call per day

Photo Credit: IntraHealth International (CC BY-NC-SA 3.0 via https://www.intrahealth.org/)

New Fast Algorithm: Collapsing Bandits

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





New Directions in Restless Bandits

Restless bandits for intervention:

- *20000 subject trial*

Outline

Public Health

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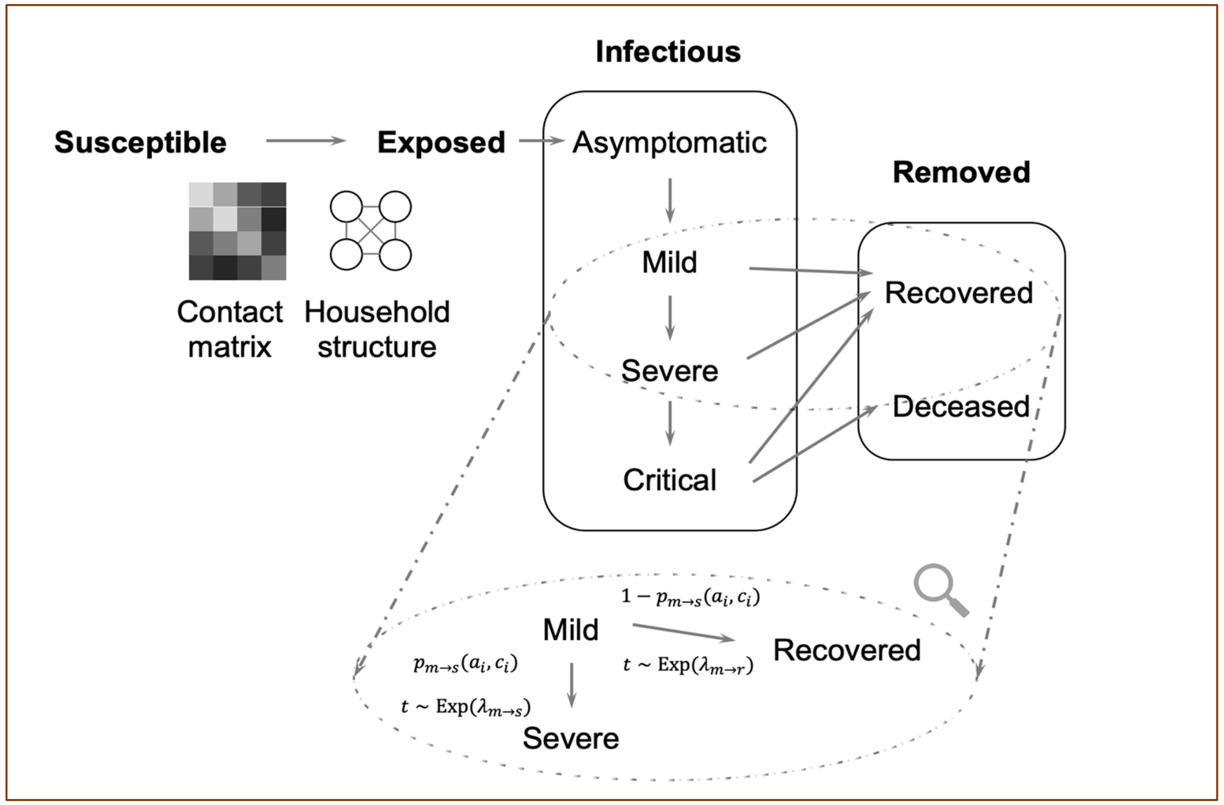
Conservation

COVID-19: Agent-based Simulation Model

Wilder

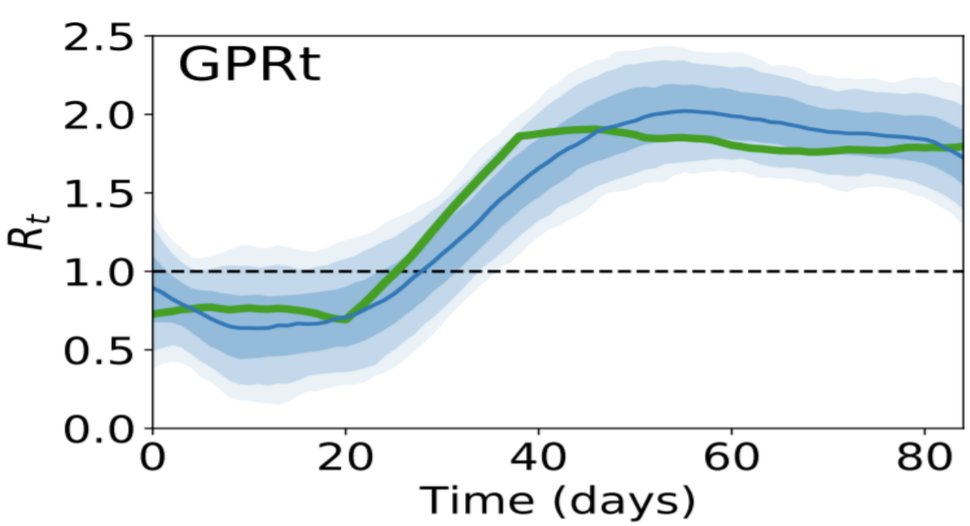


RESEARCH ARTICLE

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,[1] Michael Mina[2], Milind Tambe[1]
[1] John A. Paulson School of Engineering and Applied Sciences, Harvard University
[2] T.H. Chan School of Public Health, Harvard University
bwilder@g.harvard.edu, mmina@hsph.harvard.edu, milind_tambe@harvard.edu

Wilder

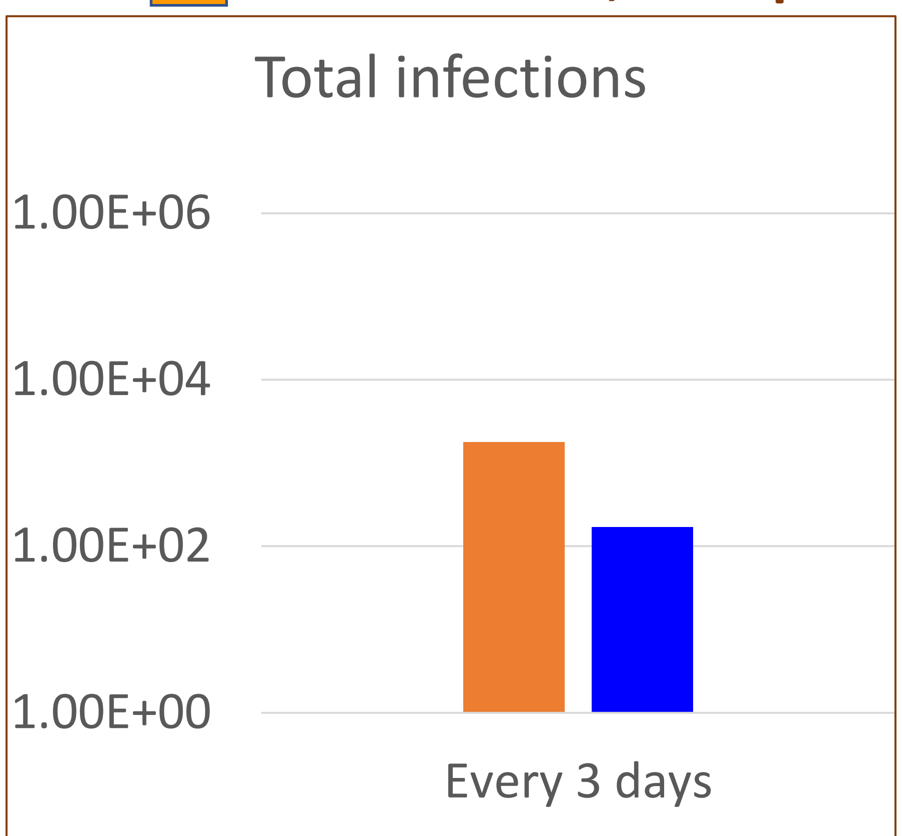
COVID Testing Policy: Accuracy vs Ease

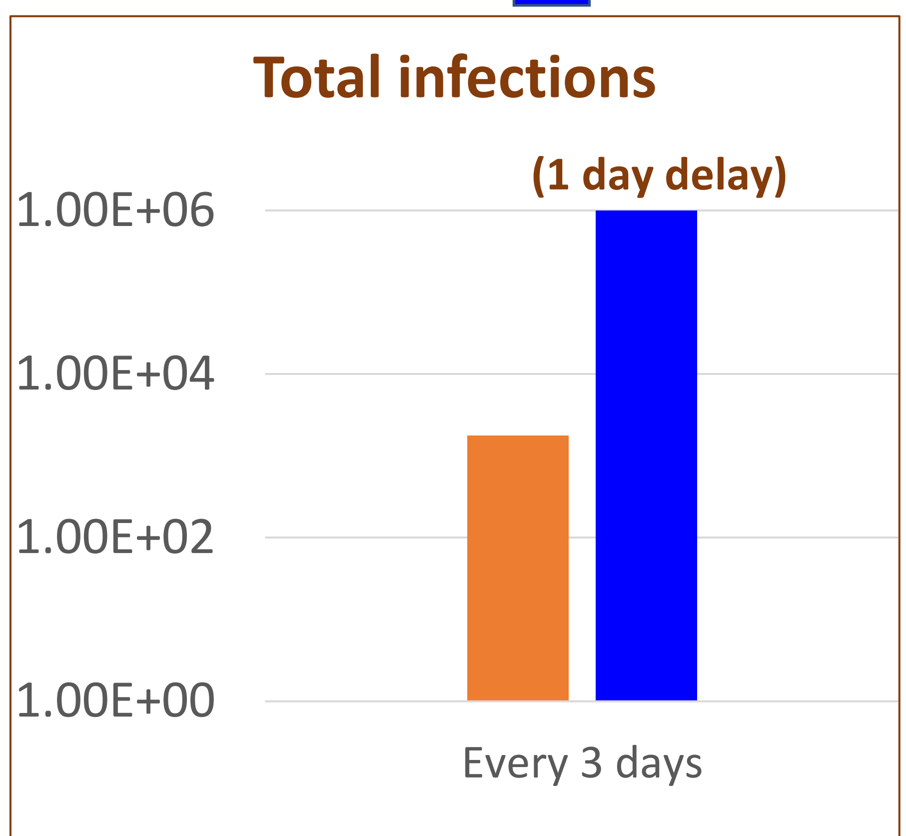
(Science Advances, 2020) with Prof. Michael Mina

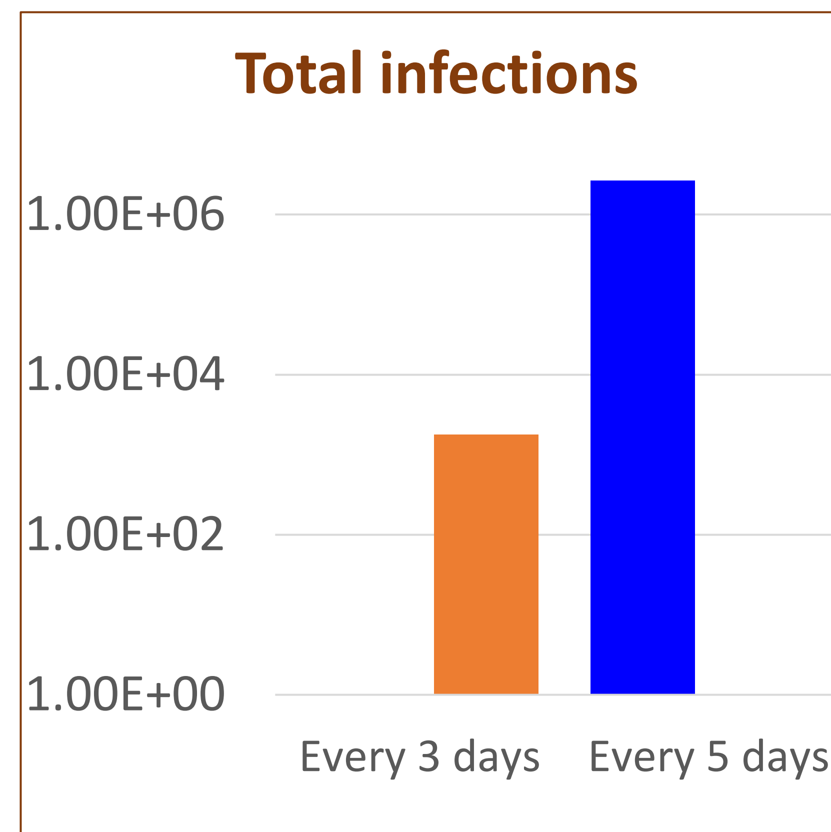
- Range of tests entering market, varying sensitivity/cost: Quantity vs Quality?
  - qRT-PCR (“gold standard”): Detect viral concentration of **10^3**/mL, \$50-100
  - Antigen strip (“Less sensitive”): **10^6**/mL, \$3-5

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

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







COVID Testing Policy: Impact

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


TIME PERSON OF THE YEAR 2020 FRONTLINE HEALTH WORKERS RACIAL-JUSTICE ORGANIZERS NEWSLETTER

IDEAS • COVID-19

America Needs to Radically Rethink Our COVID-19 Testing Approach


The New York Times

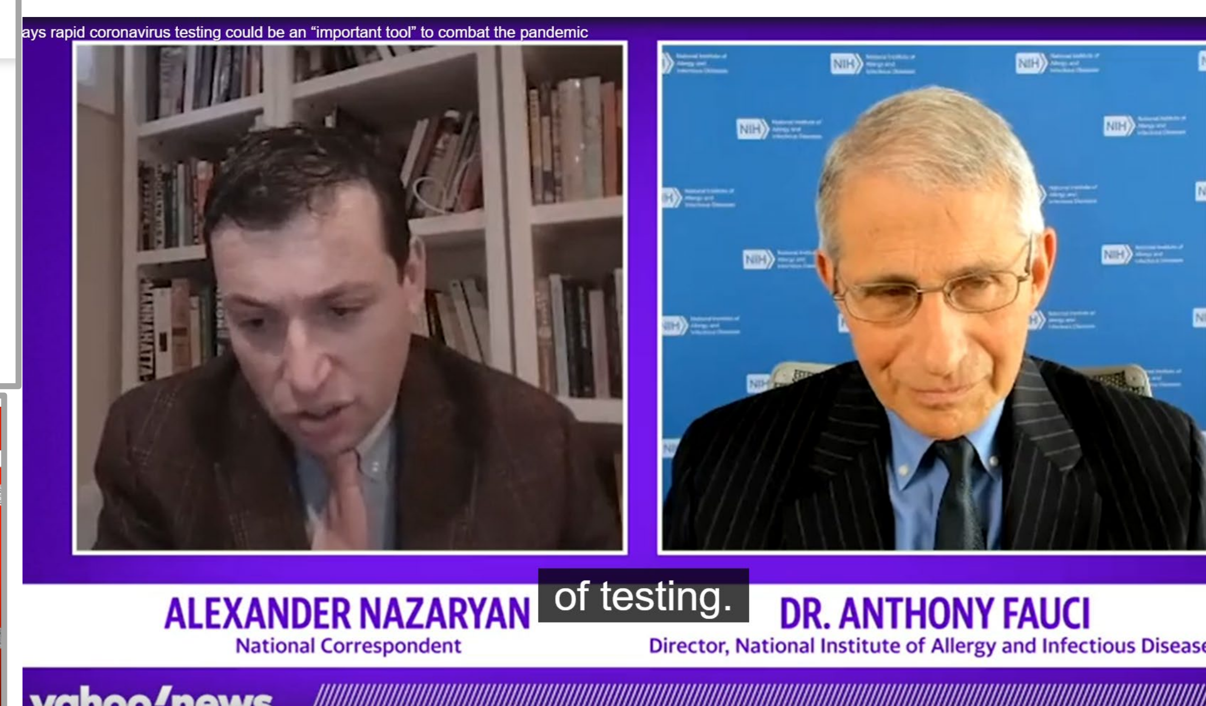
The Coronavirus Outbreak › LIVE Latest Updates Maps and Cases The Latest Vaccine Information The Thanksgiving Effect

'It's Kitchen Sink Time': Fast, Less-Accurate Coronavirus Tests May Be Good Enough


Popular Latest *The Atlantic* My Account Give a Gift

The Plan That Could Give Us Our Lives Back

The U.S. has never had enough coronavirus tests. Now a group of epidemiologists, economists, and dreamers is plotting a new strategy to defeat the virus, even before a vaccine is found.



Outline

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)

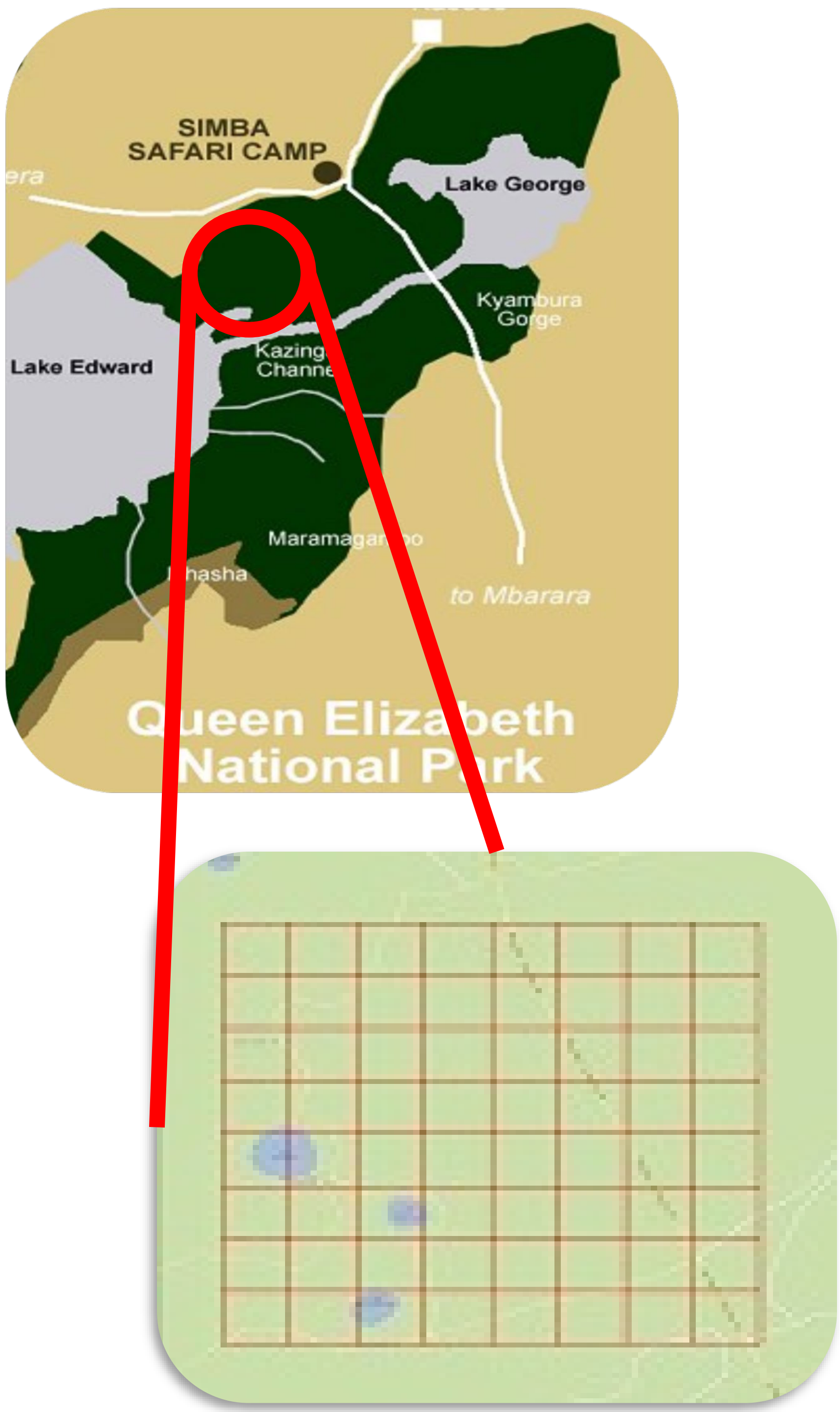
Fang

Snare or Trap

Wire snares

From Stackelberg Security Games to Green Security Games

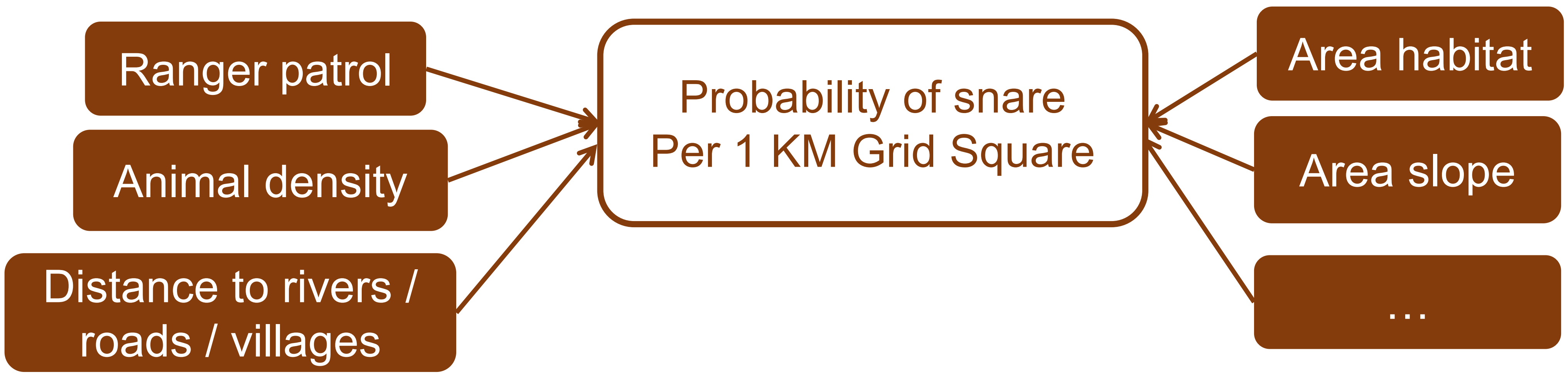
(IJCAI 2015)

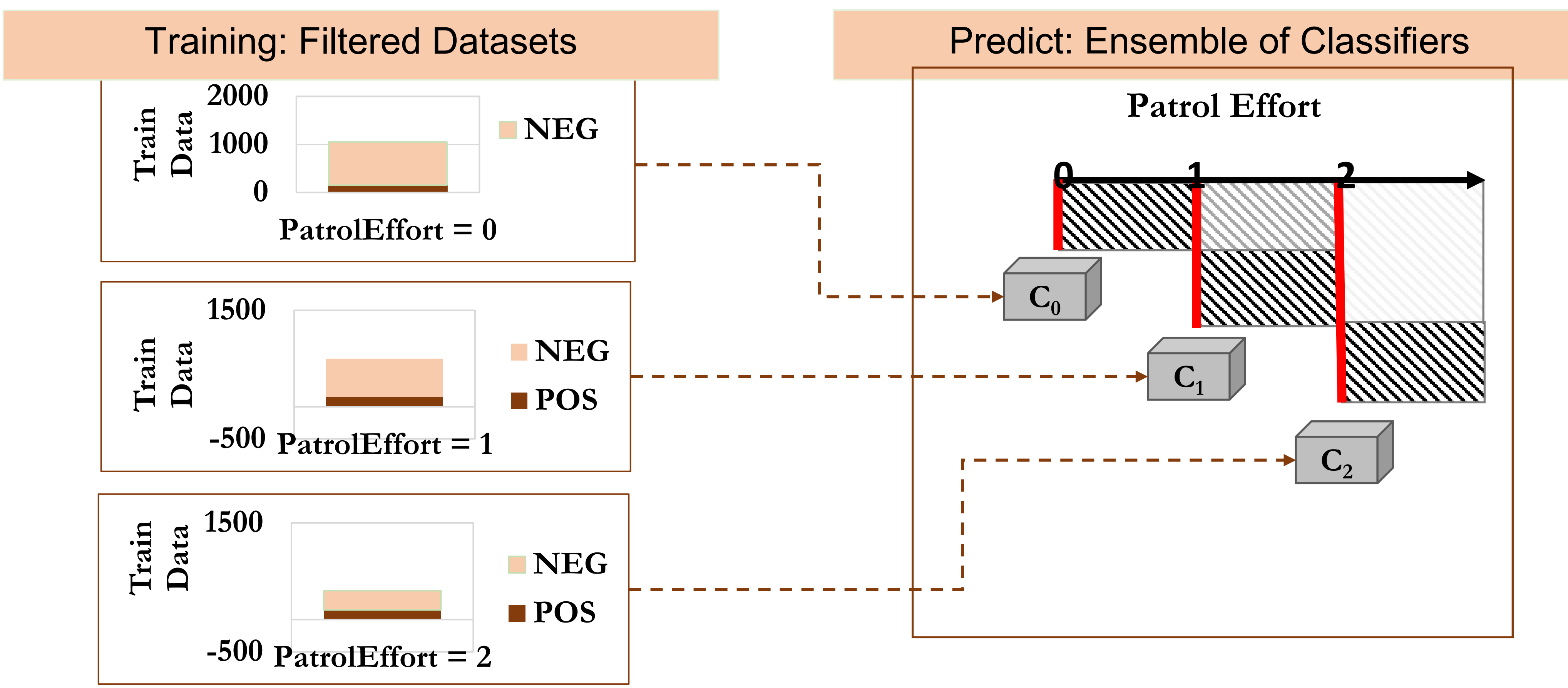


- ➢ ***Learn poacher response model at each target***
- ➢ ***So can figure out response by patrols***

Learning Adversary Response Model: Uncertainty in Observations

Nguyen Gholami





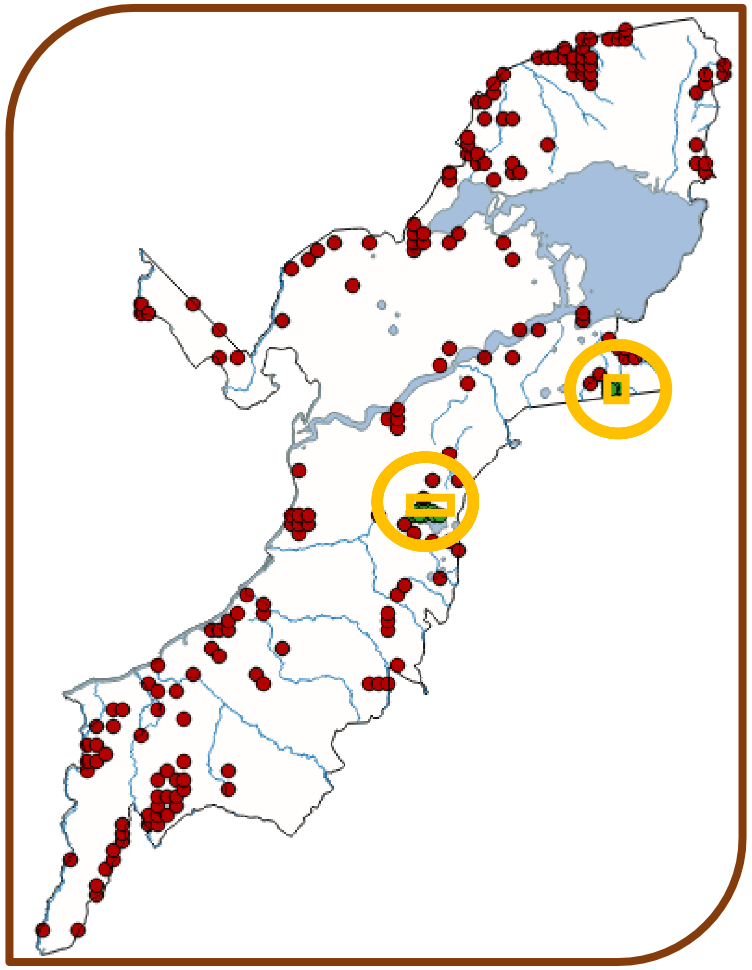
PAWS: First Pilot in the Field

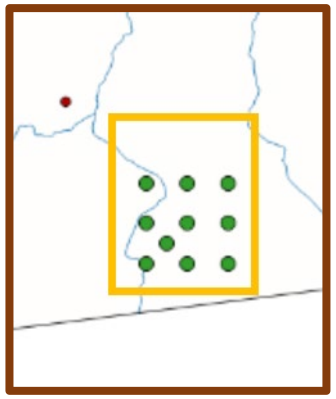
(AAMAS 2017)

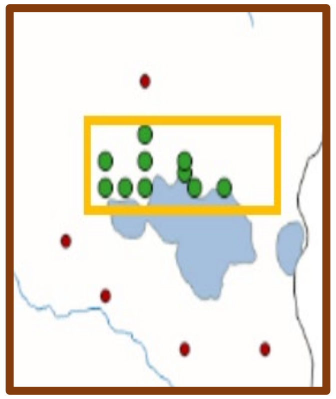

Ford


Gholami

- Two 9-sq.km areas, infrequent patrols







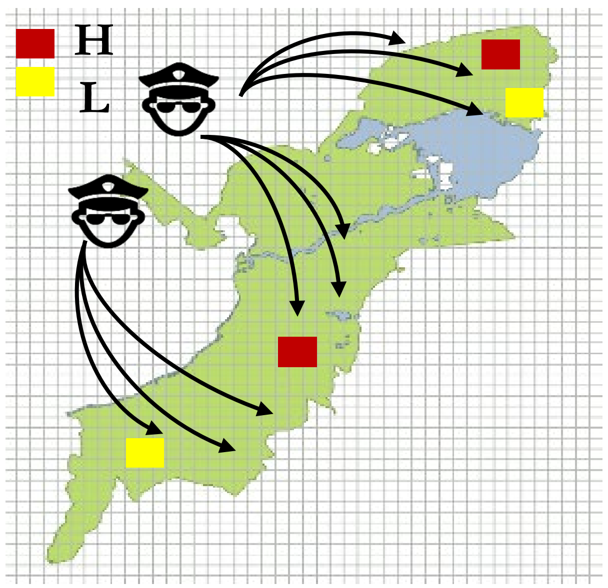
- Poached elephant
- 1 elephant snare roll
- 10 Antelope snares

PAWS Predicted High vs Low Risk Areas: 3 National Parks, 24 areas each, 6 months

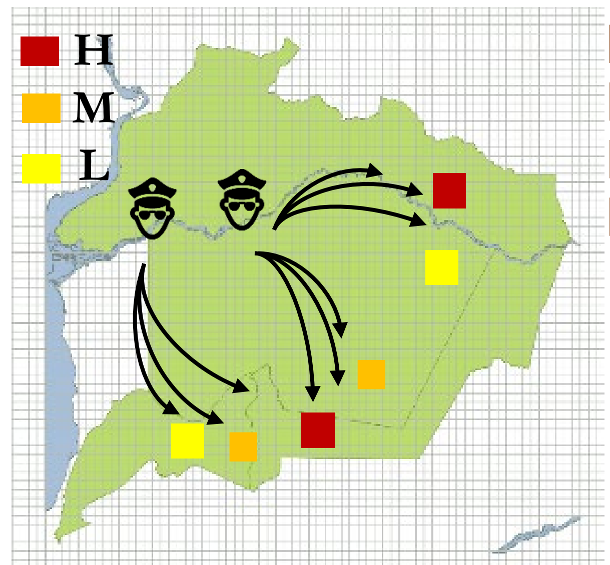
(ECML PKDD 2017, ICDE 2020)


Xu

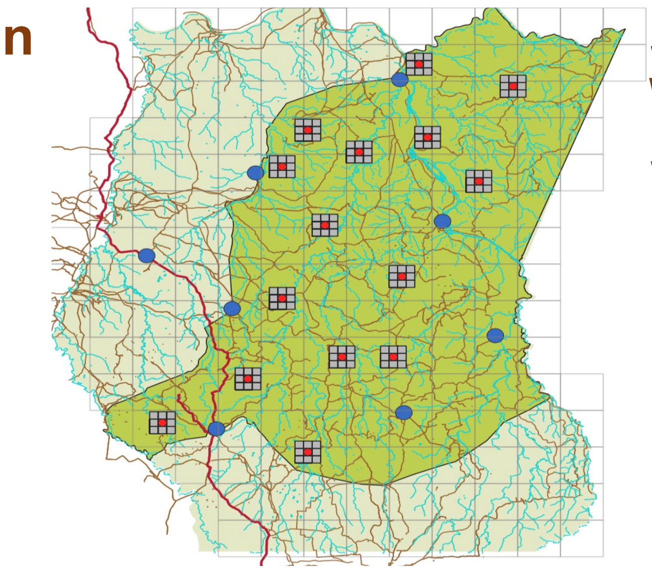

Gholami



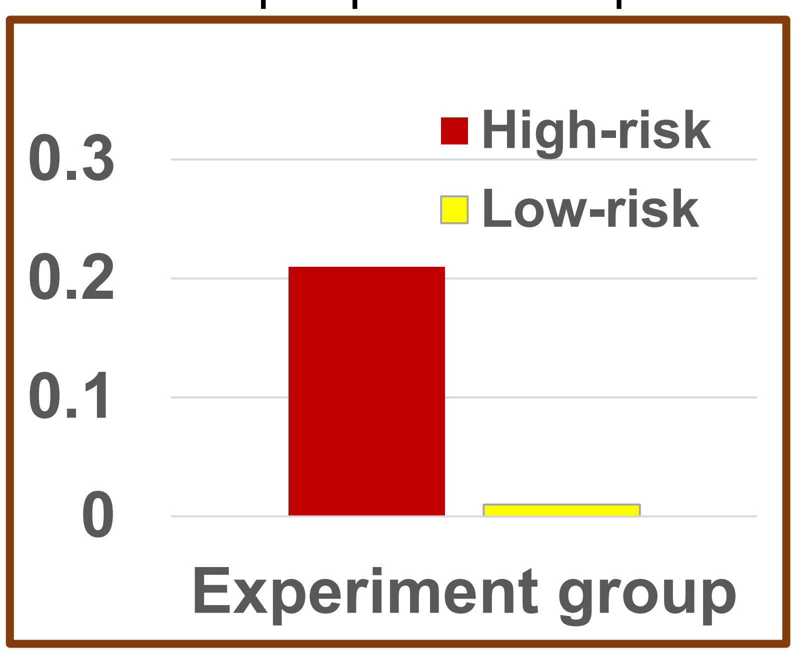
Queen Elizabeth National Park



Murchison Falls National Park


Srepok Wildlife Sanctuary

Snares per patrolled sq. KM



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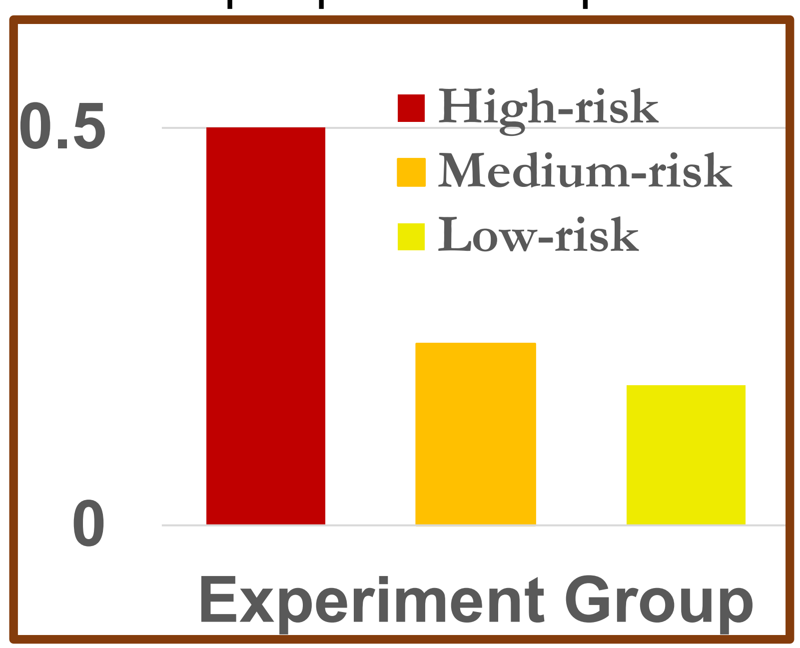

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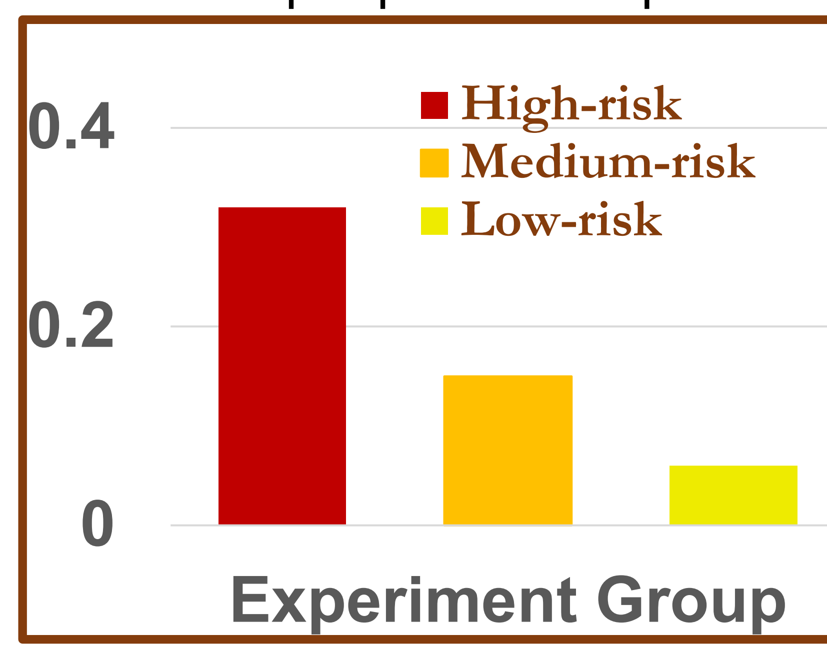


PAWS Real-world Deployment Cambodia: Srepok Wildlife Sanctuary

(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!!

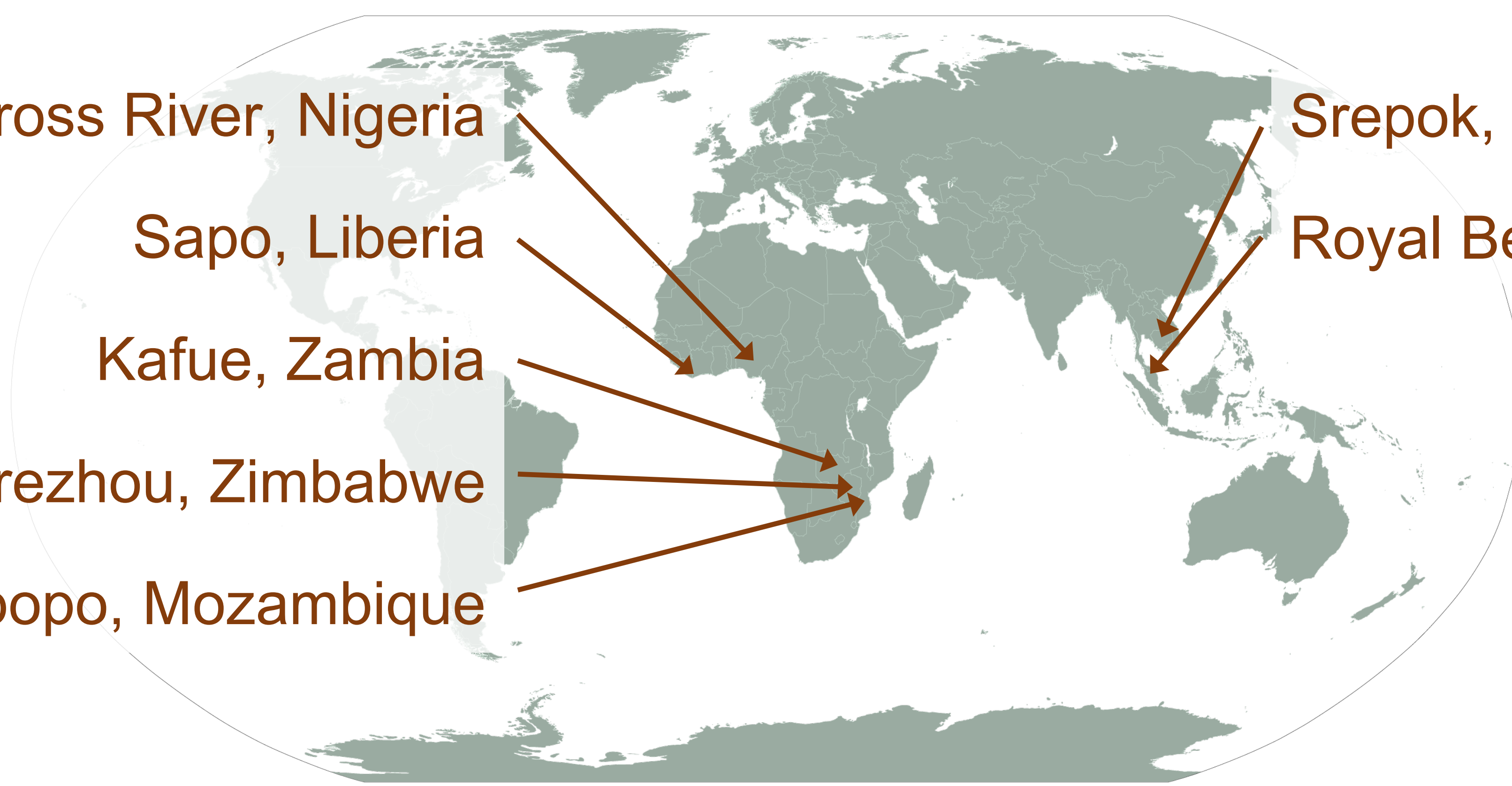
SMART

WWF

PEACE PARKS FOUNDATION · THE GLOBAL SOLUTION

WCS

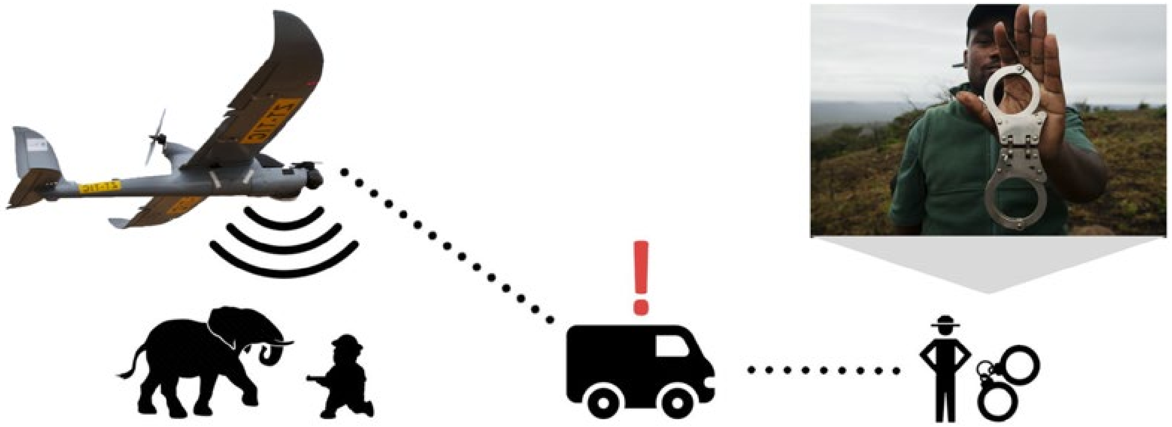
Protect Wildlife
800 National Parks
Around the Globe

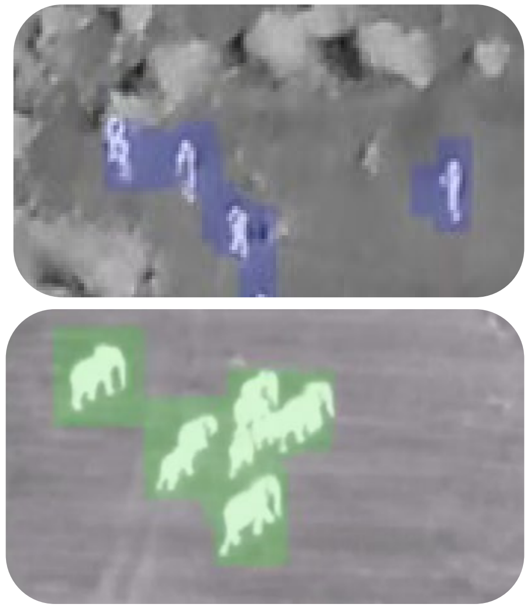


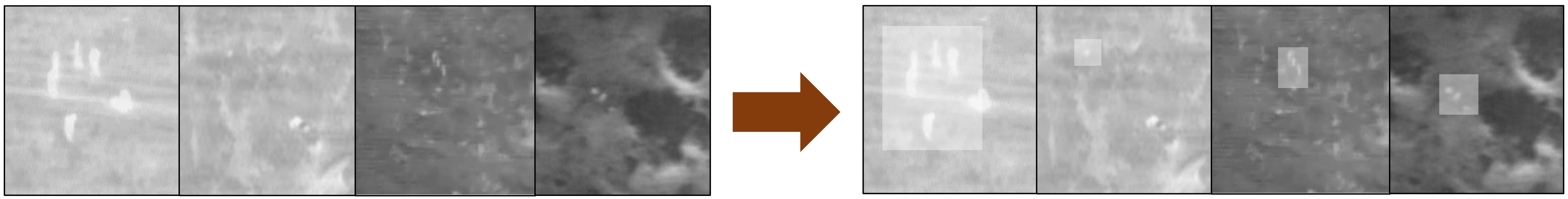
Direction #1:
Integrating Real-Time "SPOT" Information

(IAAI 2018)

Bondi

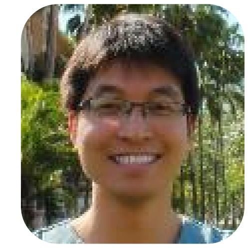






Goal: automatically find poachers

Drone Used to Inform Rangers

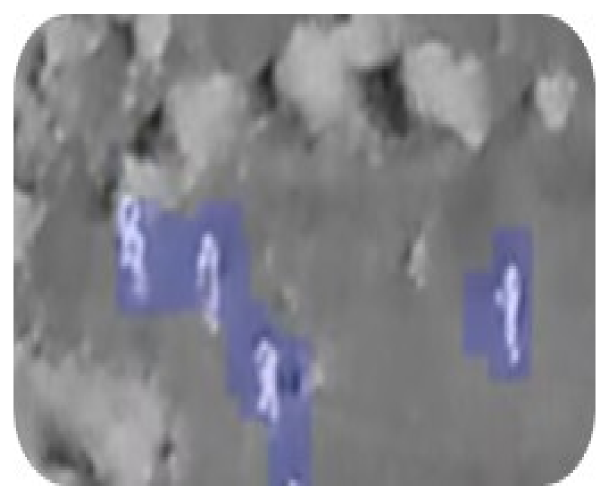


Xu

Bondi

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

Air Shepherd
The Lindbergh Foundation



Prob(ranger) = 0.3

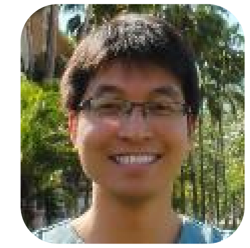
Drone Used to Inform Rangers


Xu


Bondi

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

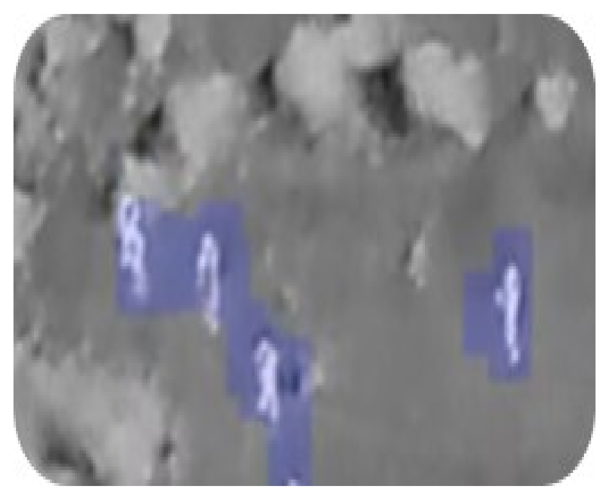
Drone Used to Inform Rangers


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

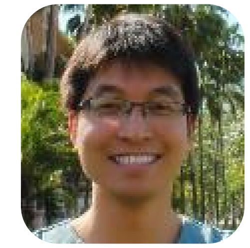
Air Shepherd
The Lindbergh Foundation



Prob(ranger) = 0.3

Exploiting Informational Advantage
Defender Knows Pure & Mixed Strategy

(AAAI 2018, AAAI 2020, AAMAS 2021)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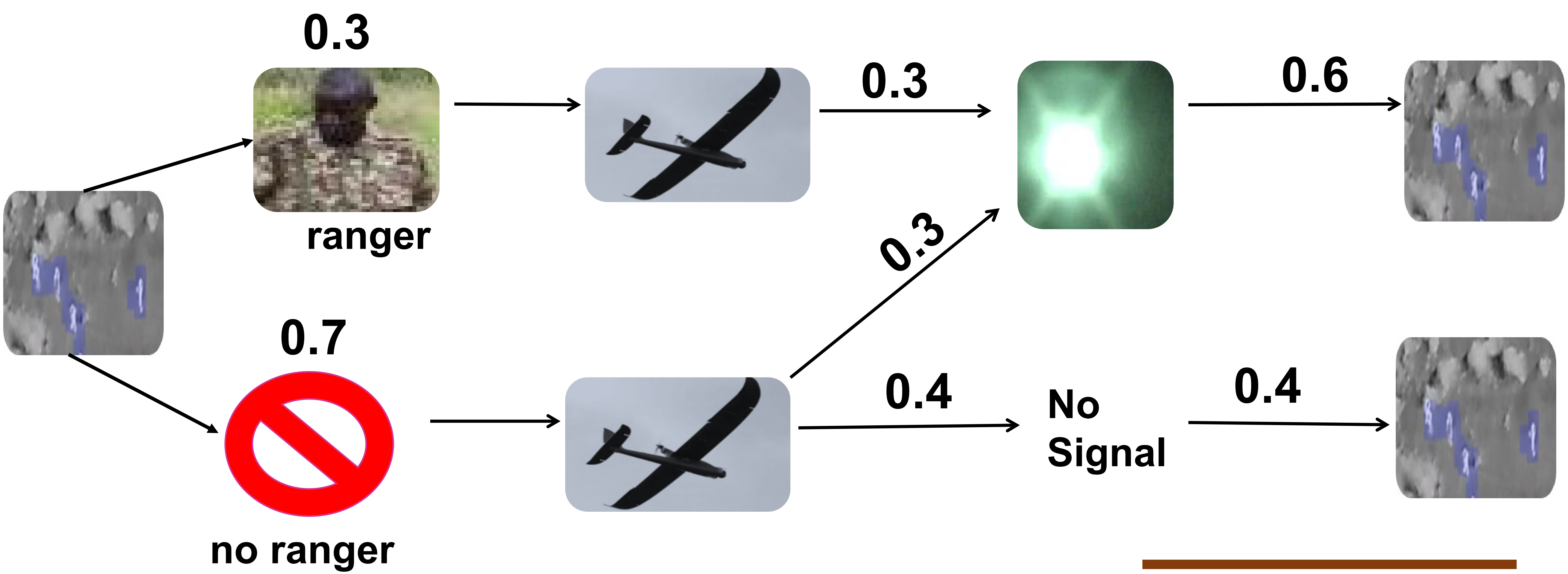
Bondi

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)



Direction #2:
Data Scarce Parks

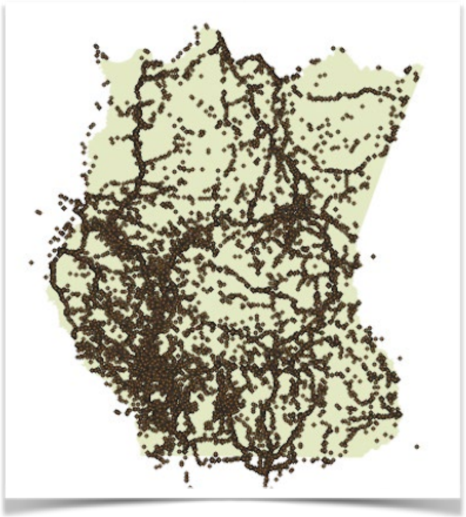

Xu

exploitation

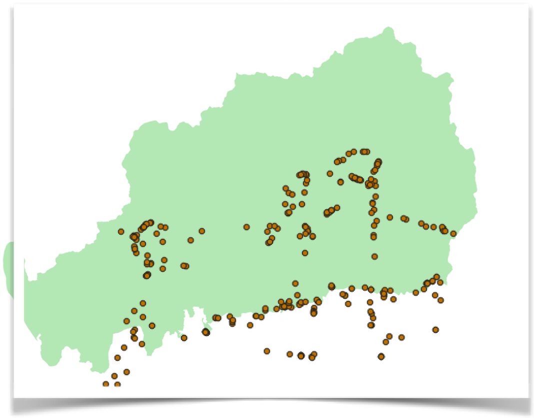
Data-rich parks: build predictive models to plan patrols

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

exploration



Srepok, Cambodia
43,269 patrol observations
2013 – 2018



Royal Belum, Malaysia
824 patrol observations
June – August 2018

LIZARD: Multiarmed Bandit
LIpschitZ Arms with Reward Decomposability (AAAI 2021)

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

- *Input:* N Targets with features, T Time, stochastic poacher places snares at targets
- *Output:* Specify patrol effort per target $\leq$ budget B
- Reduce regret wrt OPT, optimal patrol effort, for capturing snares

Lizard exploits decomposability, smoothness, monotonicity

Future: AI for Social Impact (AI4SG or AI4SI)

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)

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

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