Applying AI in preventative health interventions: Algorithms, deployments and fairness

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&

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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:

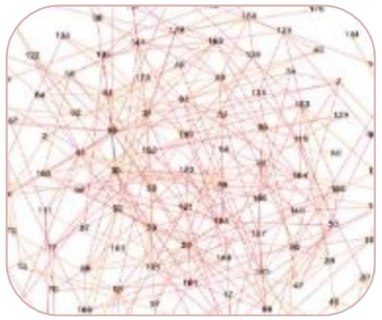
Optimize Our Limited Intervention Resources when Interacting with Other Agents

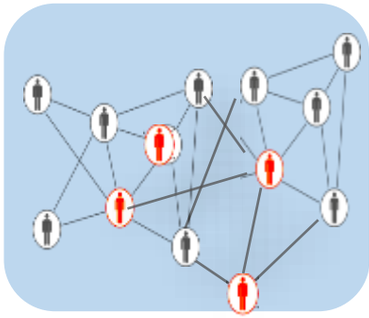
Multiagent Systems Reasoning:

Social Networks, Game Theory

Public Health
Optimizing Limited Intervention (Health Worker) Resources

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…

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

Wildlife Conservation Society

WWF

United States Coast Guard
U.S. Department of Homeland Security

Transportation Security Administration

LOS ANGELES LGBT CENTER

S.P.Y
safe place for youth

my friend's place

everwell

SMART

Air Shepherd
The Lindbergh Foundation

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

Wildlife Conservation Society

WWF

United States Coast Guard
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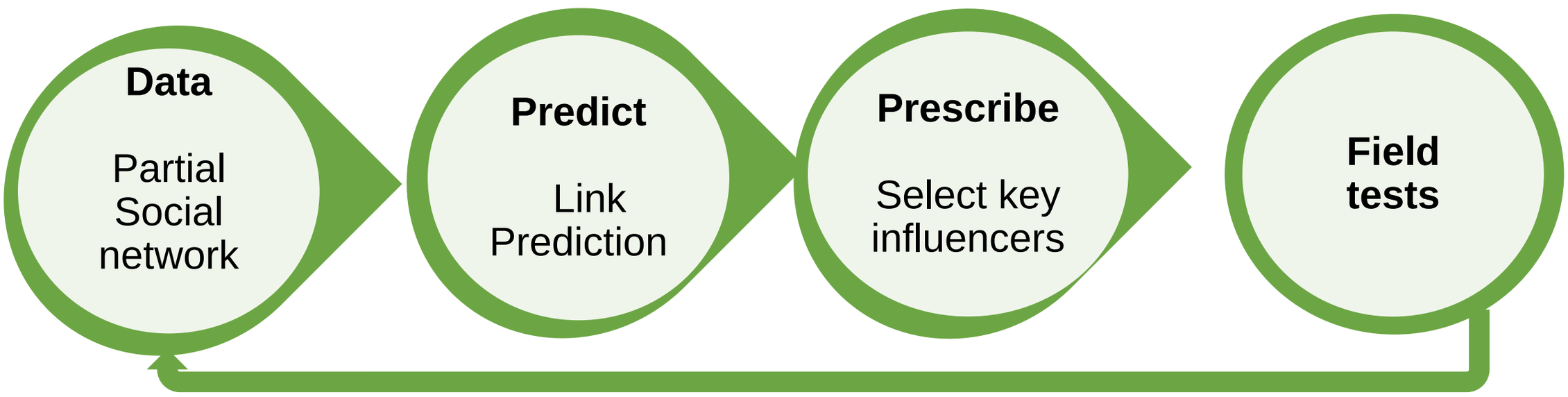
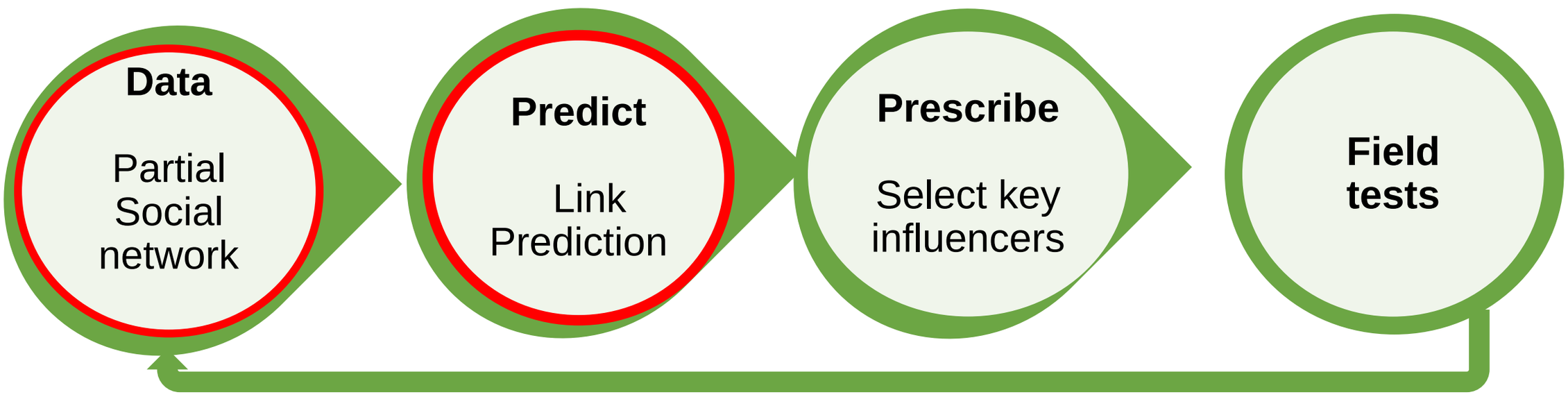
Fairness Challenges in AI for Public Health

Fairness challenges in intervention; not just prediction



Fairness Challenges in AI for Public Health

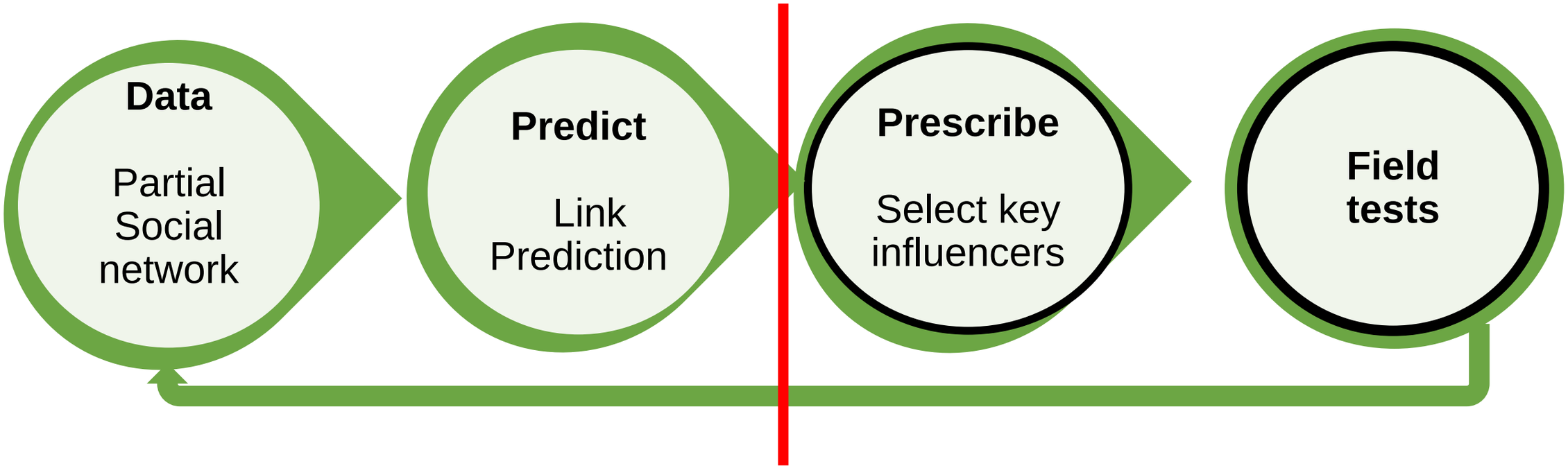
Fairness challenges in intervention; not just prediction



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

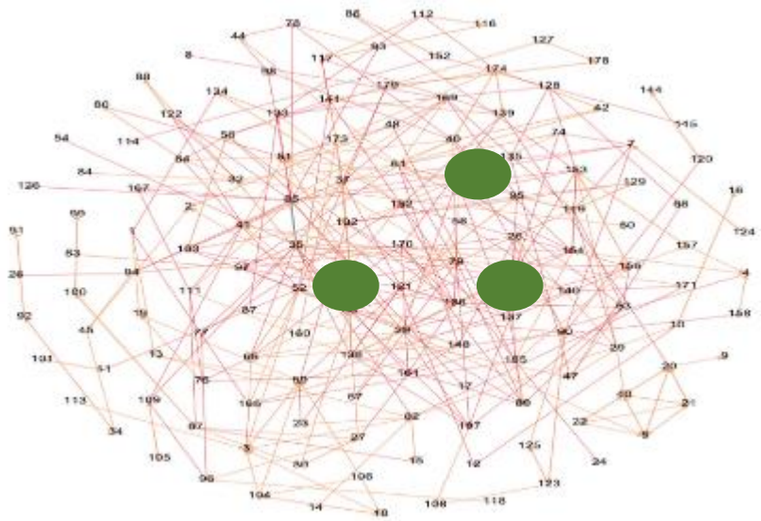
PhD student photos in top right corner

Public Health
Optimizing Limited Intervention (Social Worker) Resources

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

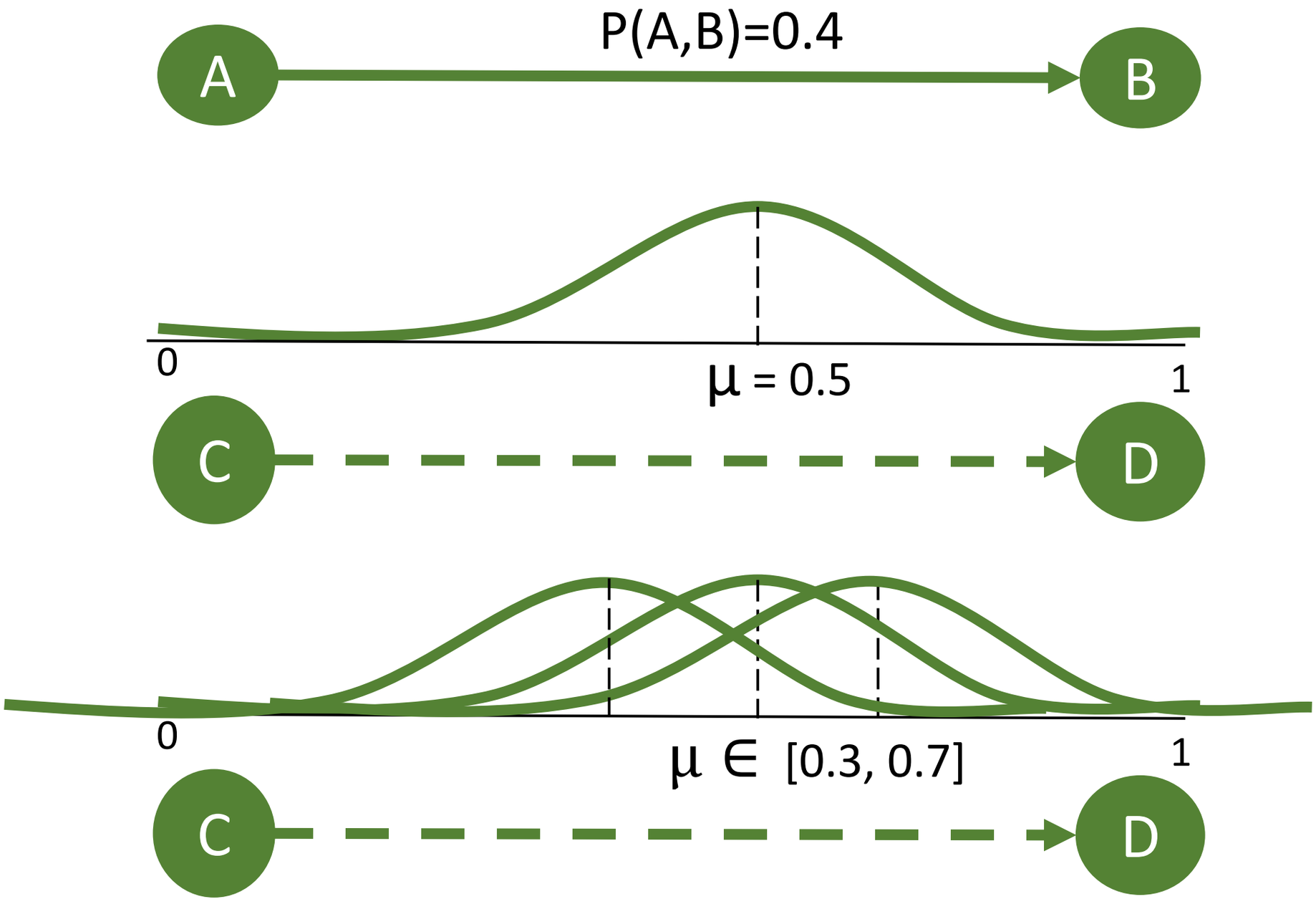
- ***Shelters**: Limited number of peer leaders to spread HIV information in social networks*
- *"Real" social networks gathered from observations in the field; not facebook etc*

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



Robust, Dynamic Influence Maximization


Wilder

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

Algorithm
Chooses policy, i.e.,
Chooses Peer leaders

vs

Nature
Chooses parameters
μ,σ

- Payoffs: (performance of algorithm)/OPT

HEALER Algorithm [2017]
Robust, Dynamic Influence Maximization


Wilder

Theorem: Converge with approximation guarantees

- Equilibrium strategy despite exponential strategy spaces: Double oracle

Nature

Influencer

	Params #1	Params #2	Params #3
Policy #1	0.8, -0.8	0.3, -0.3	0.4, -0.4
Policy #2	0.7, -0.7	0.5, -0.5	0.6, -0.6
Policy #3	0.6, -0.6	0.4, -0.4	0.7, -0.7

Influencer's oracle

\	Params #1	Params #2
Policy #1	0.8, -0.8	0.3, -0.3
Policy #2	0.7, -0.7	0.5, -0.5
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Nature's oracle

	Params #1	Params #2	Params #3
Policy #1	0.8, -0.8	0.3, -0.3	0.4, -0.4
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Challenge: Multi-step Policy


Yadav


Wilder

	Params #1	Params #2	Params #3
Policy #1	0.8, -0.8	0.3, -0.3	0.4, -0.4
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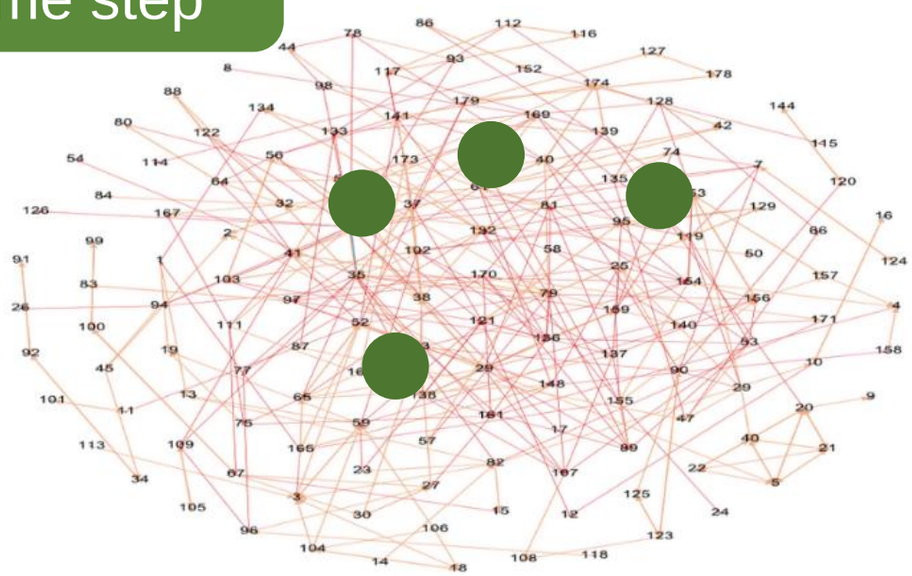
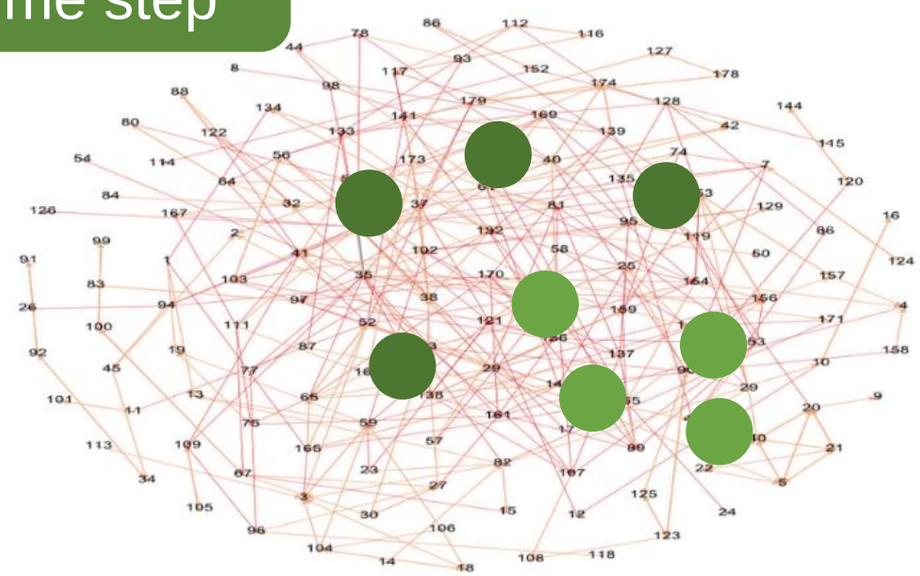
K = 4
1st time step



K = 4
2nd time step



HEALER: POMDP Model for Multi-Step Policy Robust, Dynamic Influence Maximization

Yadav

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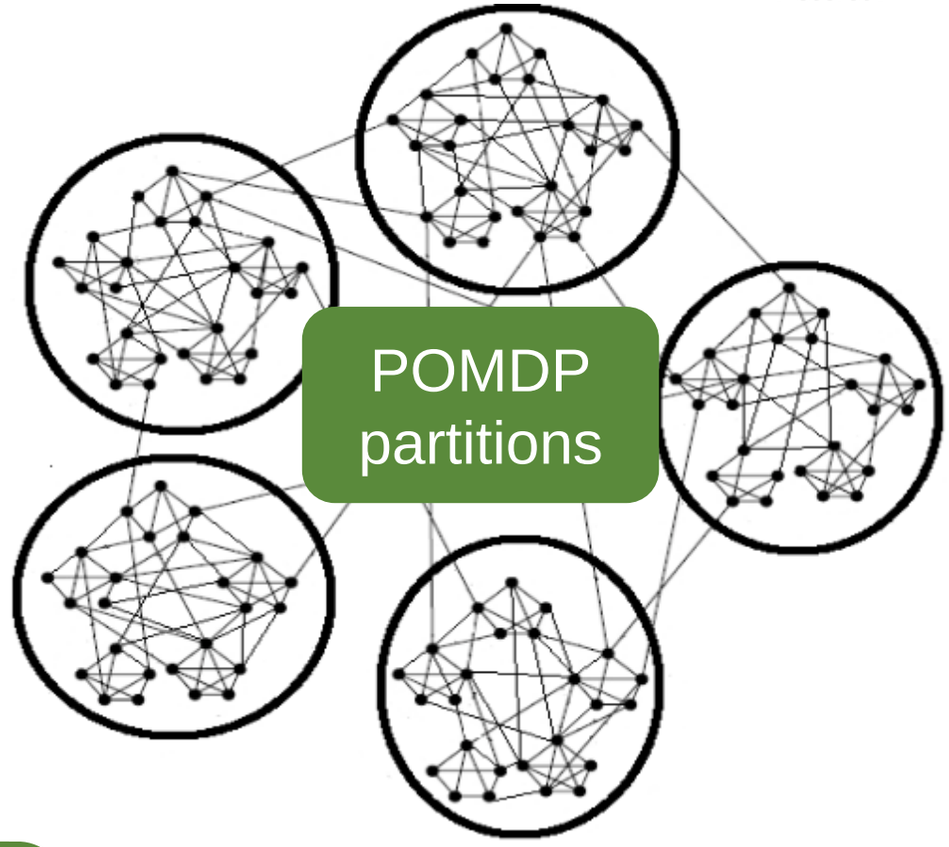

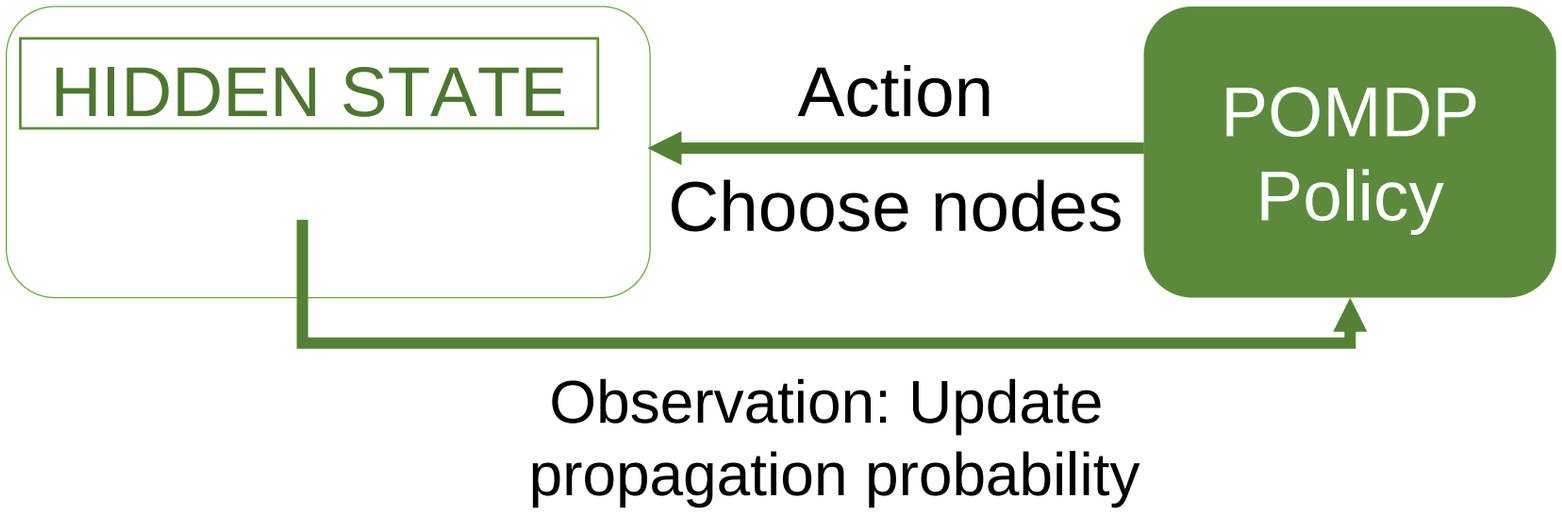

Pilot Tests with HEALER with 170 Homeless Youth [2017]


Yadav


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Recruited youths:

HEALER	HEALER++	DEGREE CENTRALITY
62	56	55

12 peer leaders

Results: Pilot Studies [2017]


Yadav


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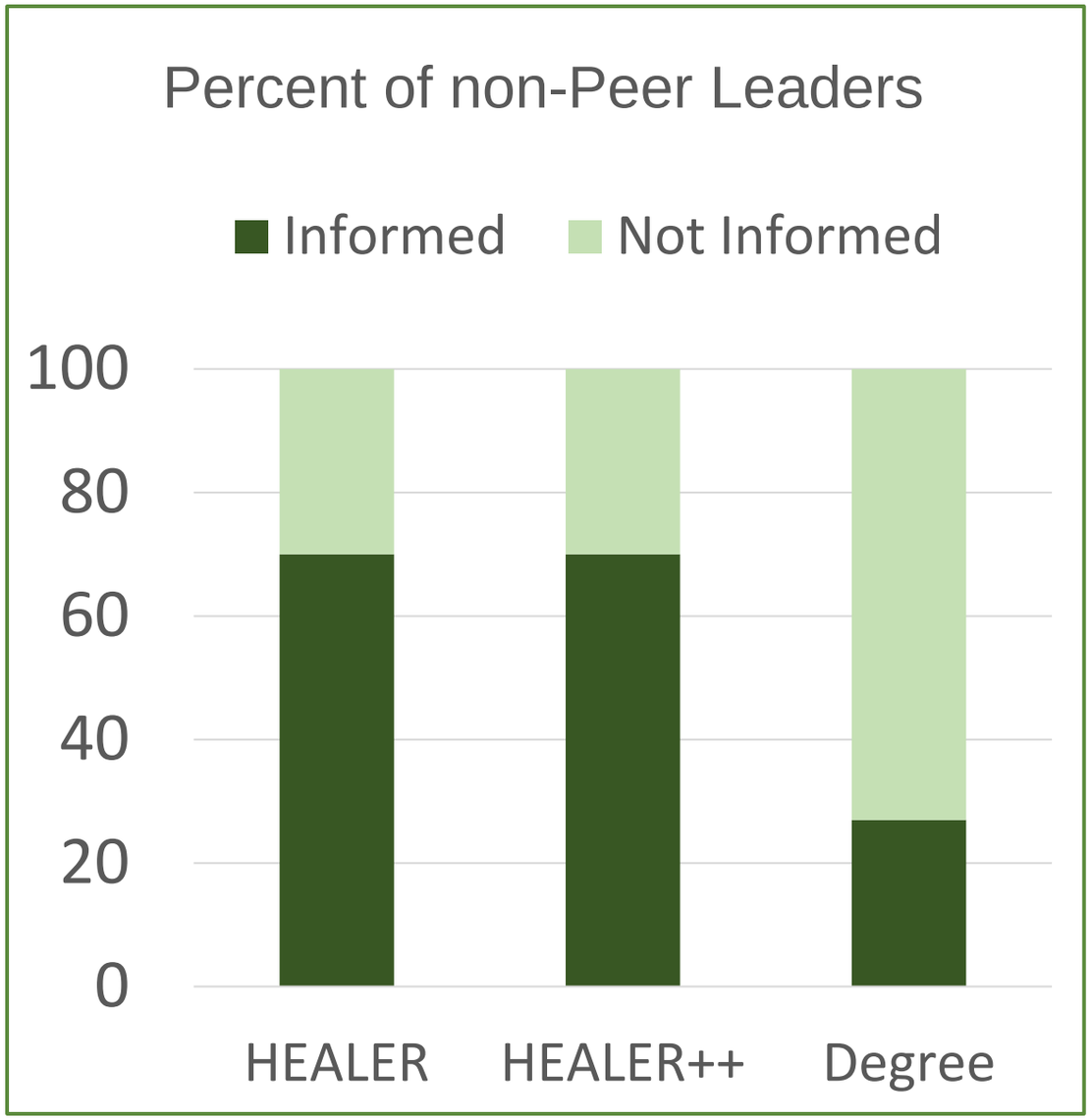
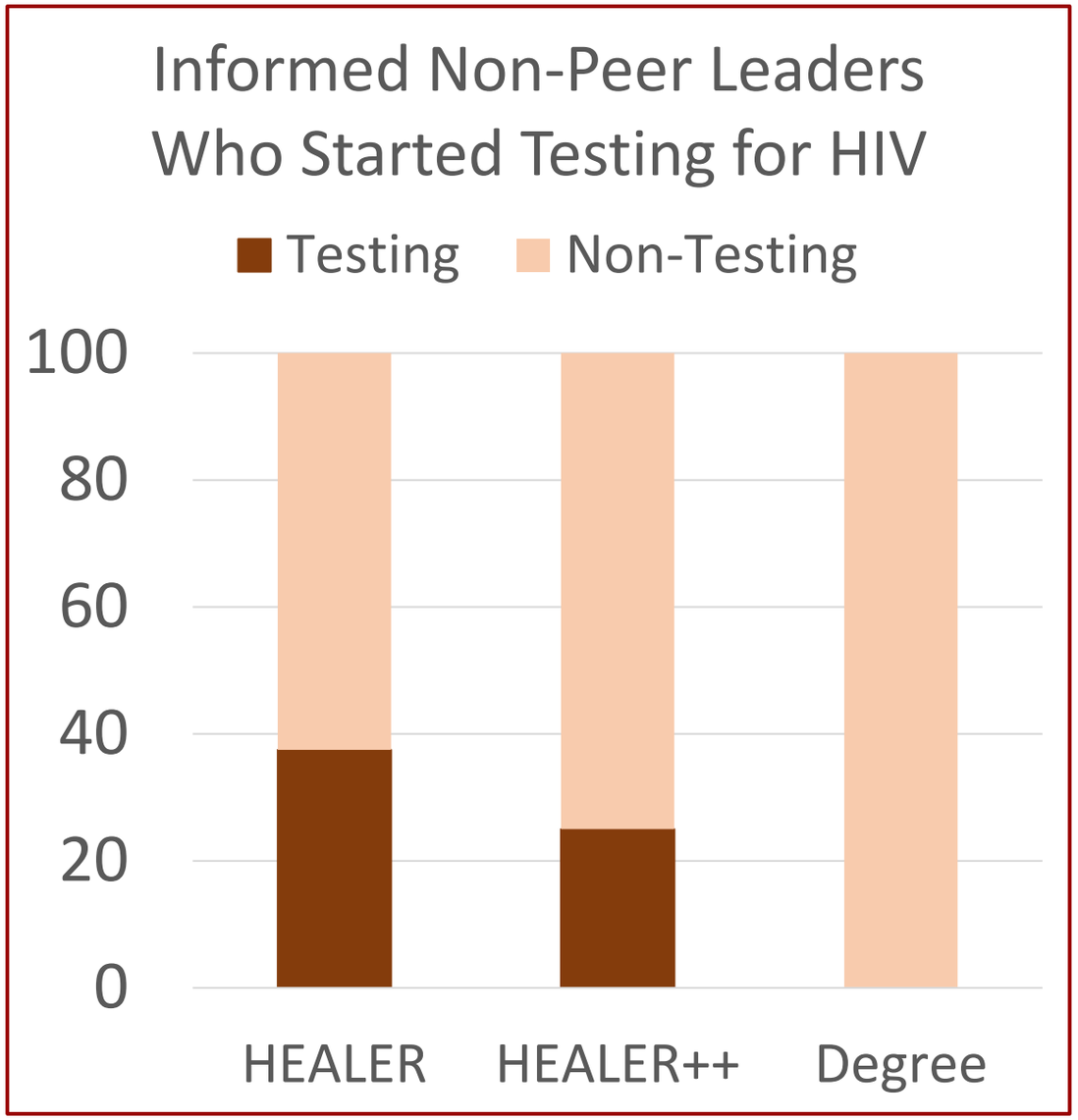


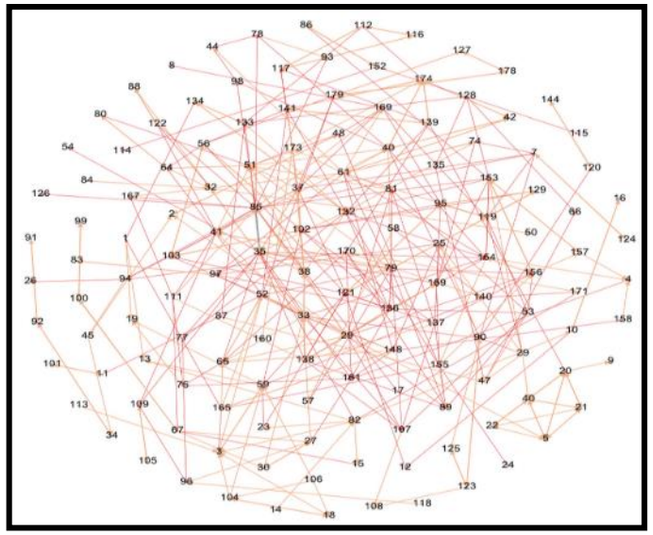


More details: Journal of Society of Social Work & Research (Nov 2018)

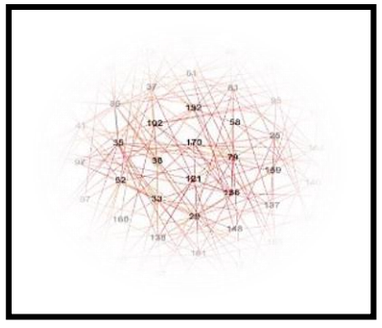
Data to Deployment Pipeline:
Network Sampling to avoid Data Collection Bottleneck

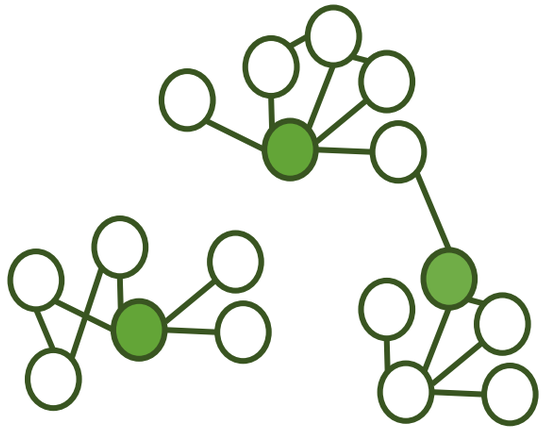

Wilder

Data collection costly



Sample 18%





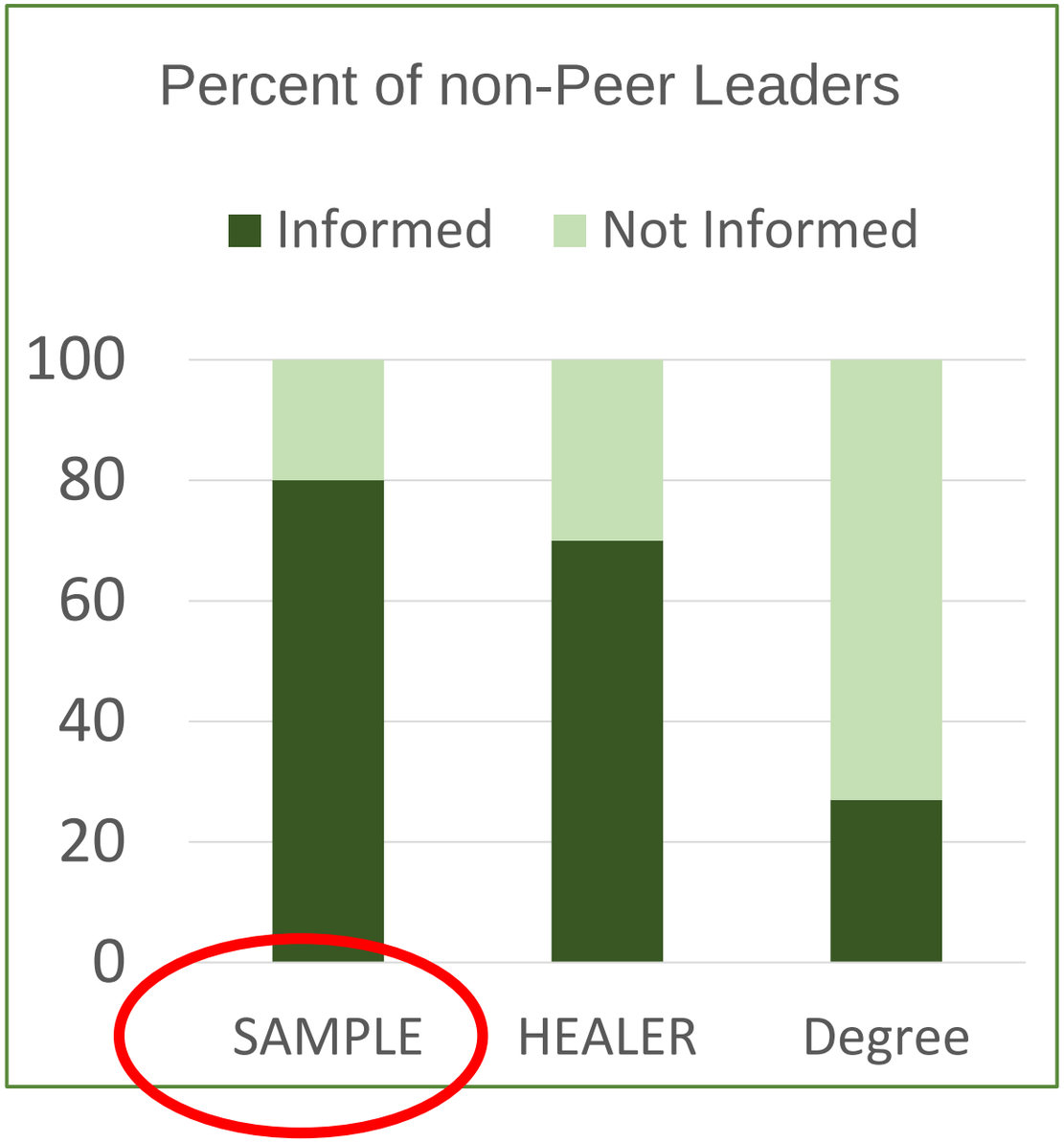
Sampling from largest communities

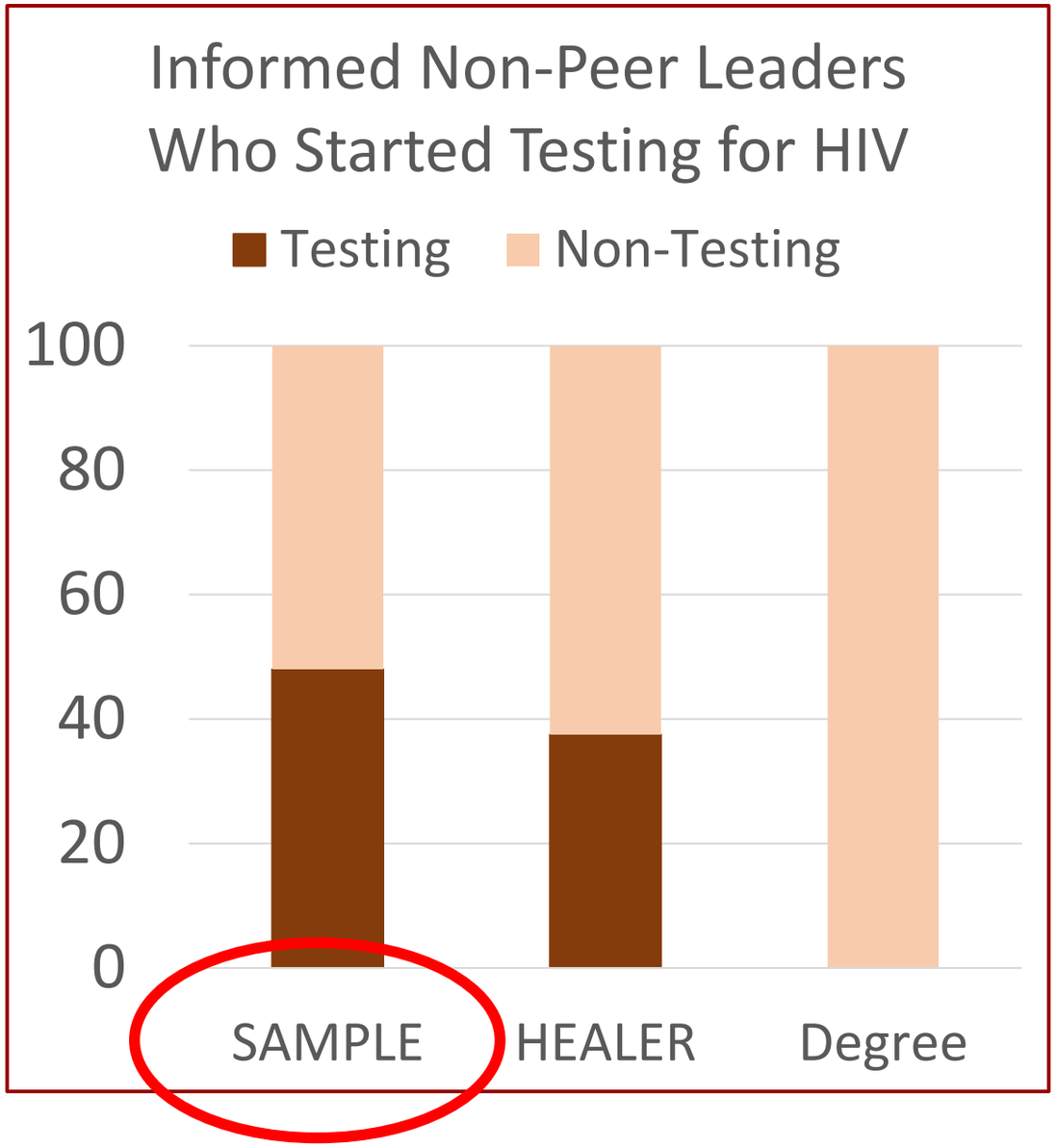
New experiment With 60 homeless youth

12 peer leaders

Results: Pilot Studies with New Sampling Algorithm [2018]

Wilder





AI Assistant: HEALER

Continuing Research on HIV prevention [2019]

- Completing 900 youth study at three homeless shelters

my friend's place

S.P.Y
safe place for youth

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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

Killian

Data Collect

Phone logs

Predict high risk patients

RF or LSTM

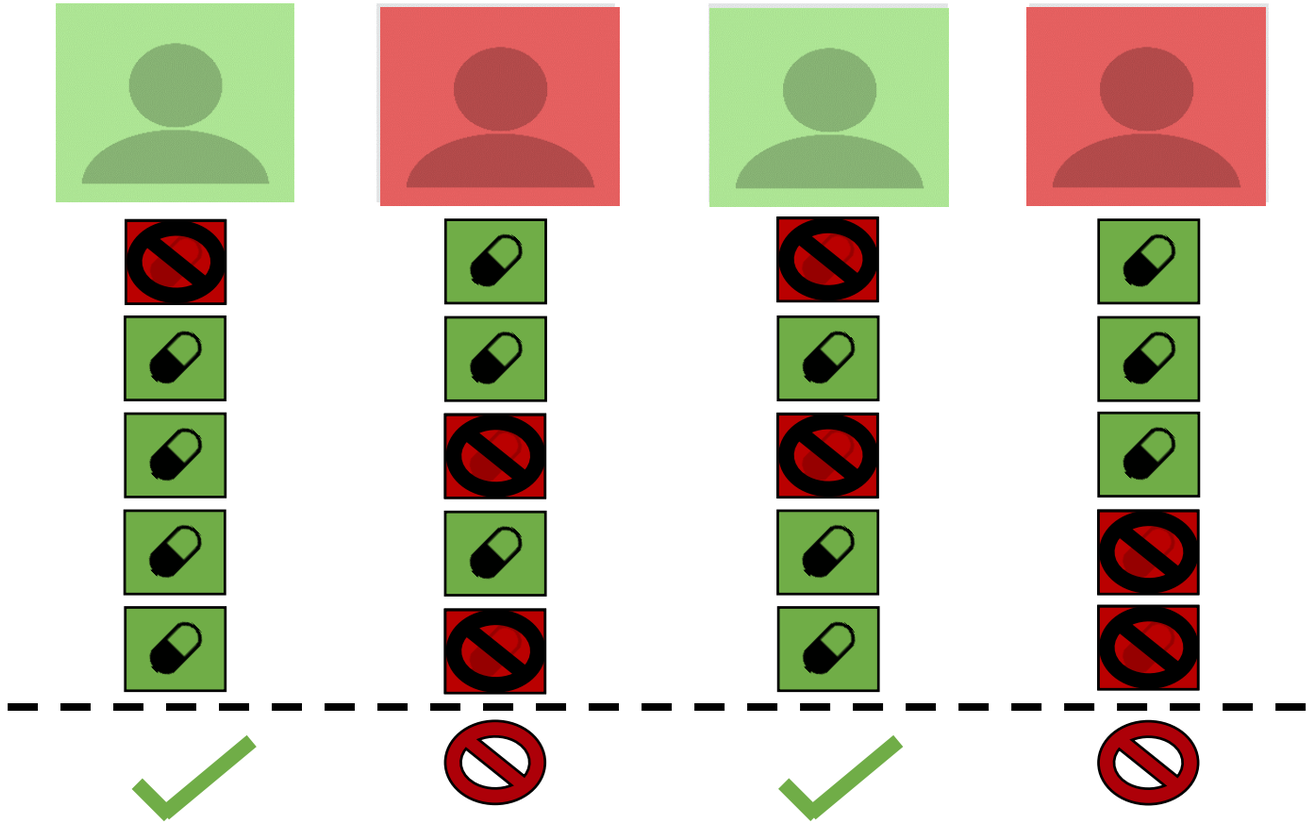
Prescription

Constraint Top K

Field

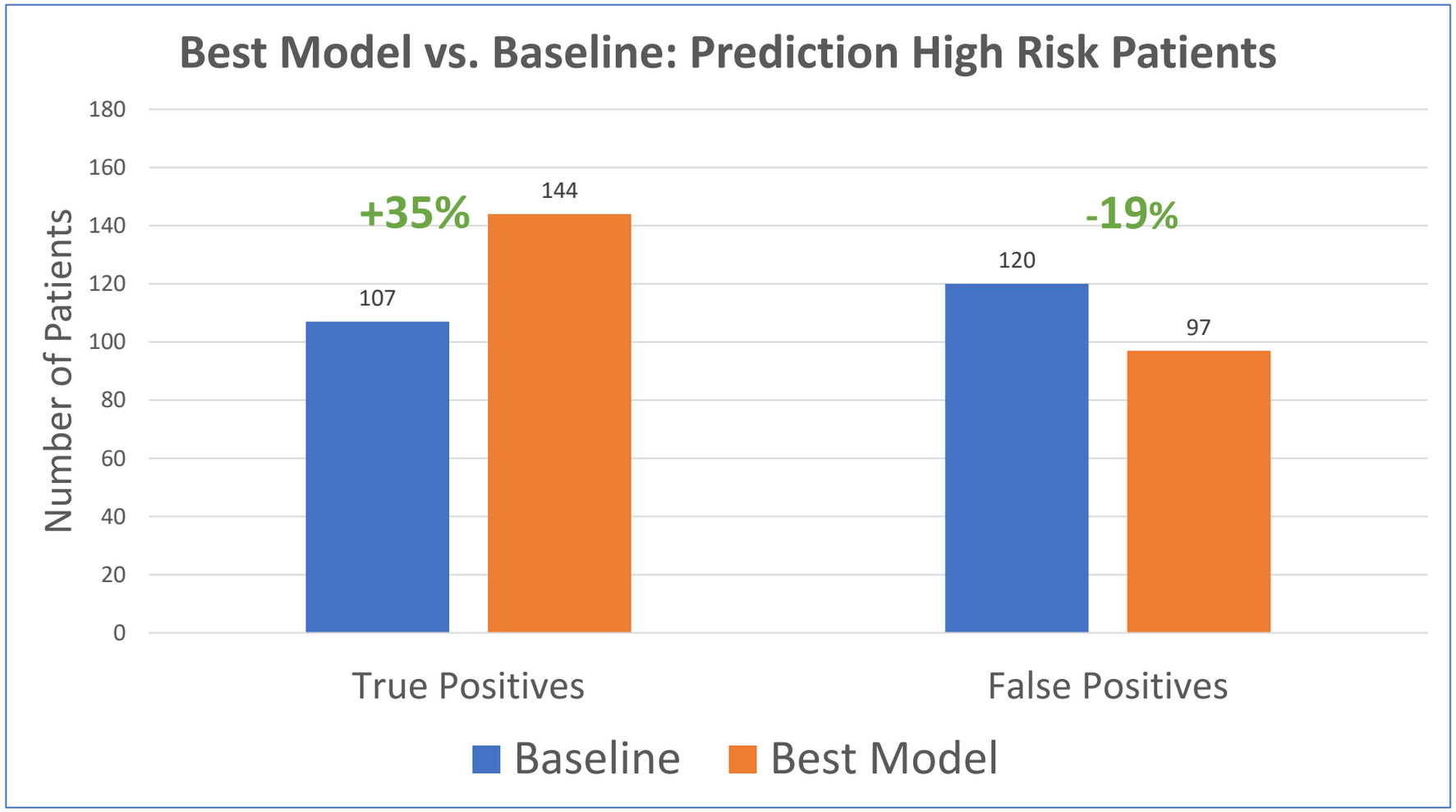
- *15K patients, 1.5M calls*

everwell



Increasing TB Treatment Adherence: Intervening before patients miss doses [2019]

Killian



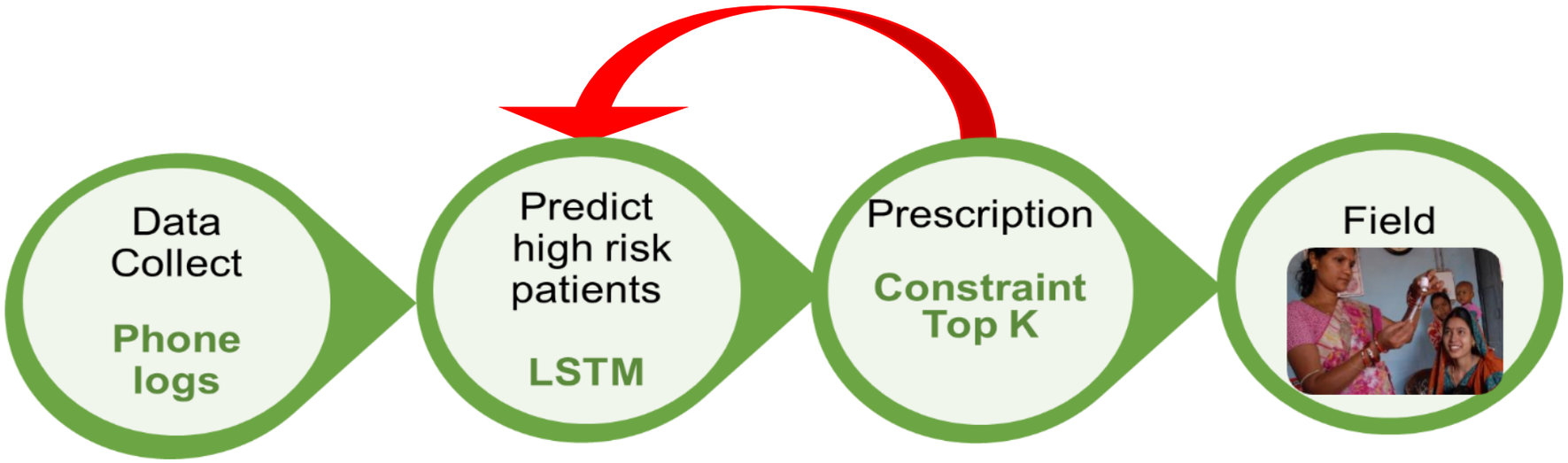
Data from

State of Maharashtra

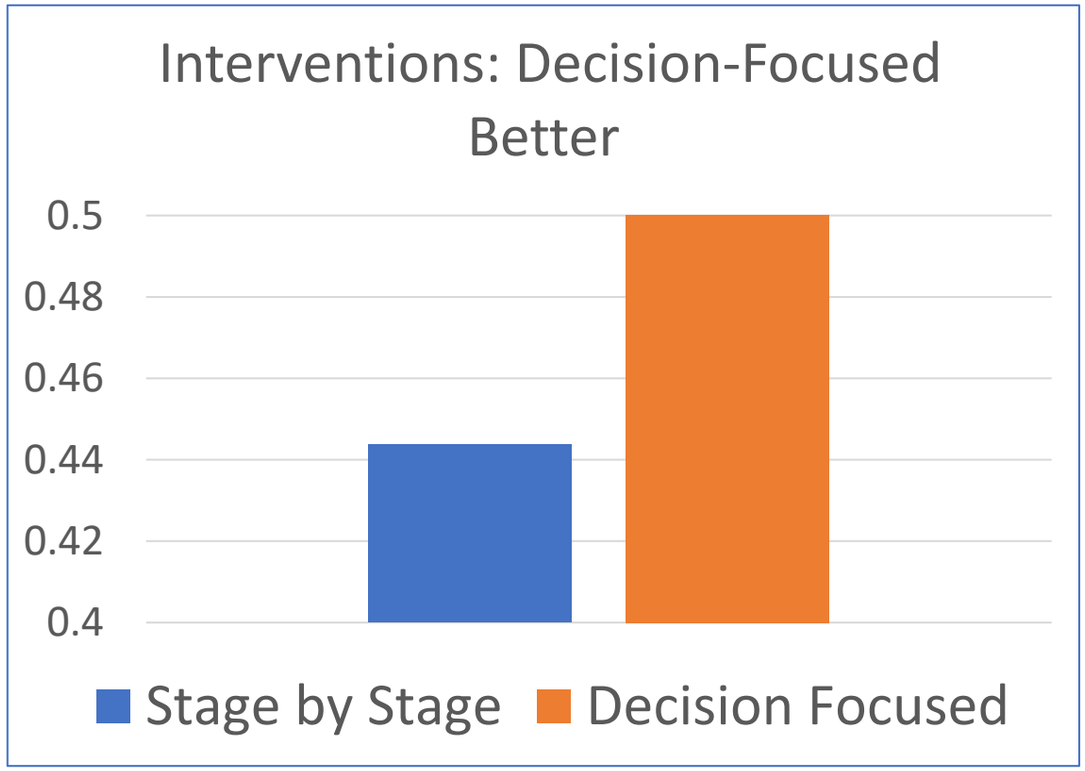
India

Improving TB interventions
Decision-Focused Methods (simultation study)

Wilder



Decision focused learning improves TB interventions



Integrating with Everwell's Platform

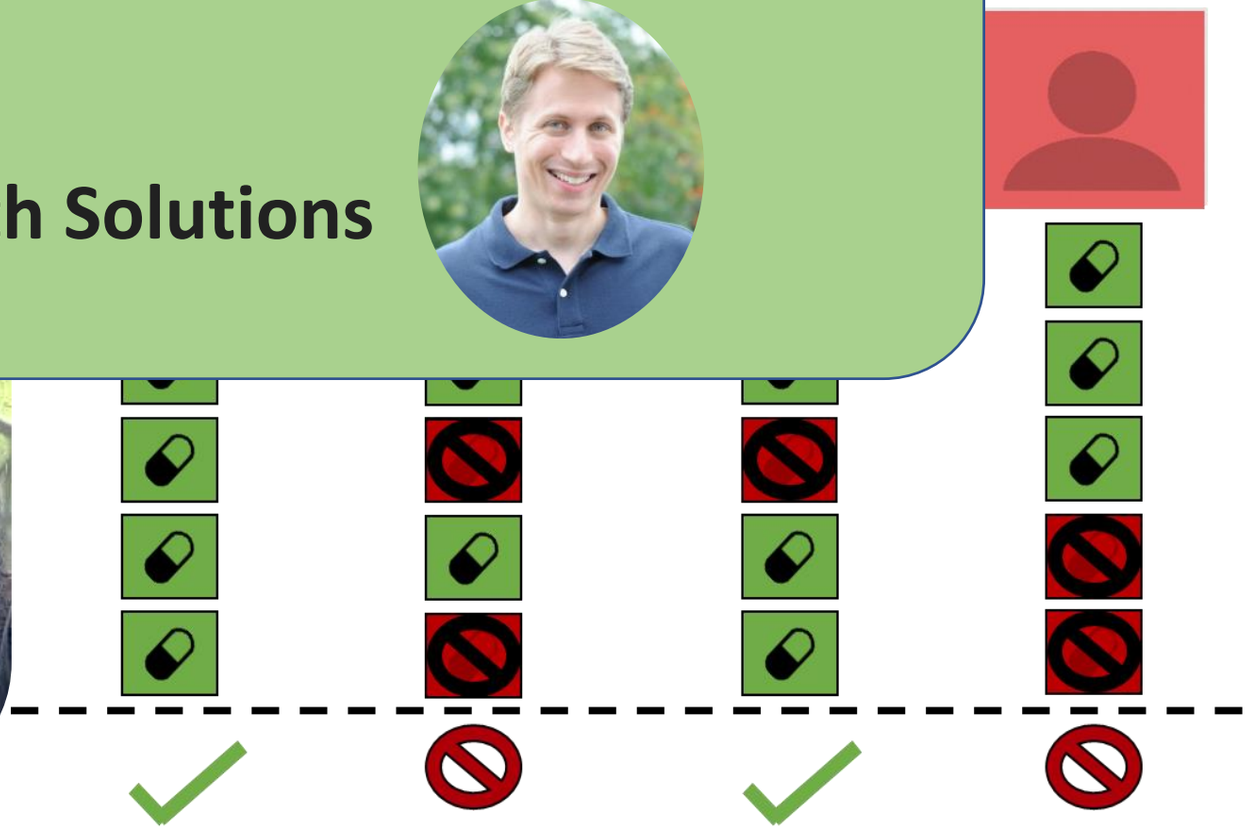
Killian

everwell

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

Rahmattalabi

- Suicide rate is significantly high among youth experiencing homelessness (~7%-26%)

Suicide Prevention in Marginalized Populations: Choose Gatekeepers in social networks

Rahmattalabi

$$\mathcal{G} = (\mathcal{N}, \mathcal{E})$$

Train: $x_n = 1$

Available: $\xi_n = 1$

Covered: $y_n(\boldsymbol{x}, \boldsymbol{\xi}) = 1$

- Worst case availability: constant-sum game against nature

Algorithm
Chooses K gatekeepers

vs

Nature
Chooses some gatekeepers to not participate

Fairness & AI for Public Health

AI and Public health

HIV prevention

TB Prevention

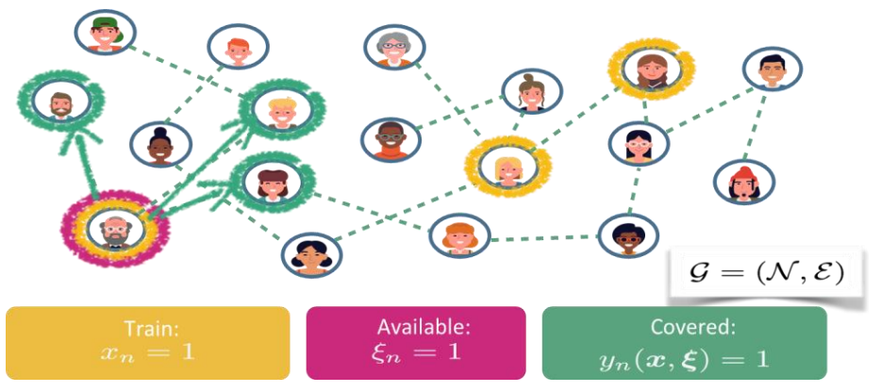
Suicide Prevention

Fairness challenges in intervention

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

Rahmattalabi

Is there any Inequality in coverage of marginalized populations?

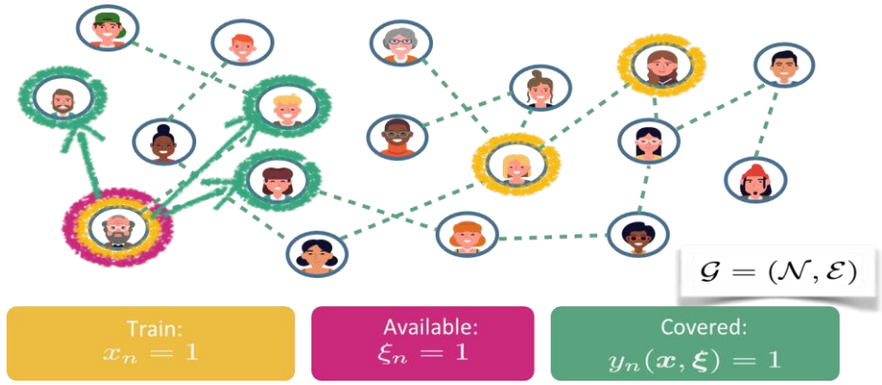


Network Name	Network Size	Percentage of covered individuals by racial group				
		White	Black	Hispanic	Mixed	Other
SPY1	95	70	36	–	86	94
SPY2	117	78	–	42	76	67
SPY3	118	88	–	33	95	69
MFP1	165	96	77	69	73	28
MFP2	182	44	85	70	77	72

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

Rahmattalabi

- Inequality in coverage of marginalized population



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MFP1	165	96	77	69	73	28

Maximin Fairness:
Towards addressing Fairness Challenges

Rahmattalabi

- Maximin fairness constraints: Every group at least W coverage

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

$$\mathcal{Y} := \left\{ \boldsymbol{y} \in \{0,1\}^N : \sum_{n\in\mathcal{N}_c} y_n \geq W|\mathcal{N}_c| \quad \forall c \in \mathcal{C}, \ \forall \boldsymbol{\xi} \in \Xi \right\}$$

Network Name	Network Size	Percentage of covered individuals by racial group				
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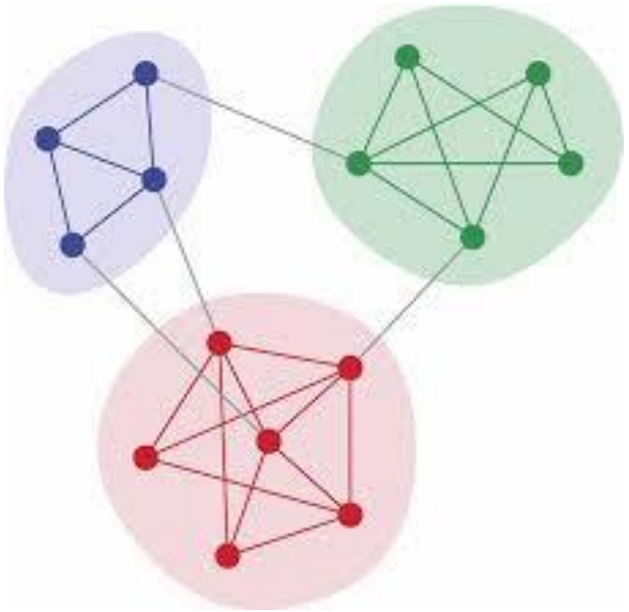
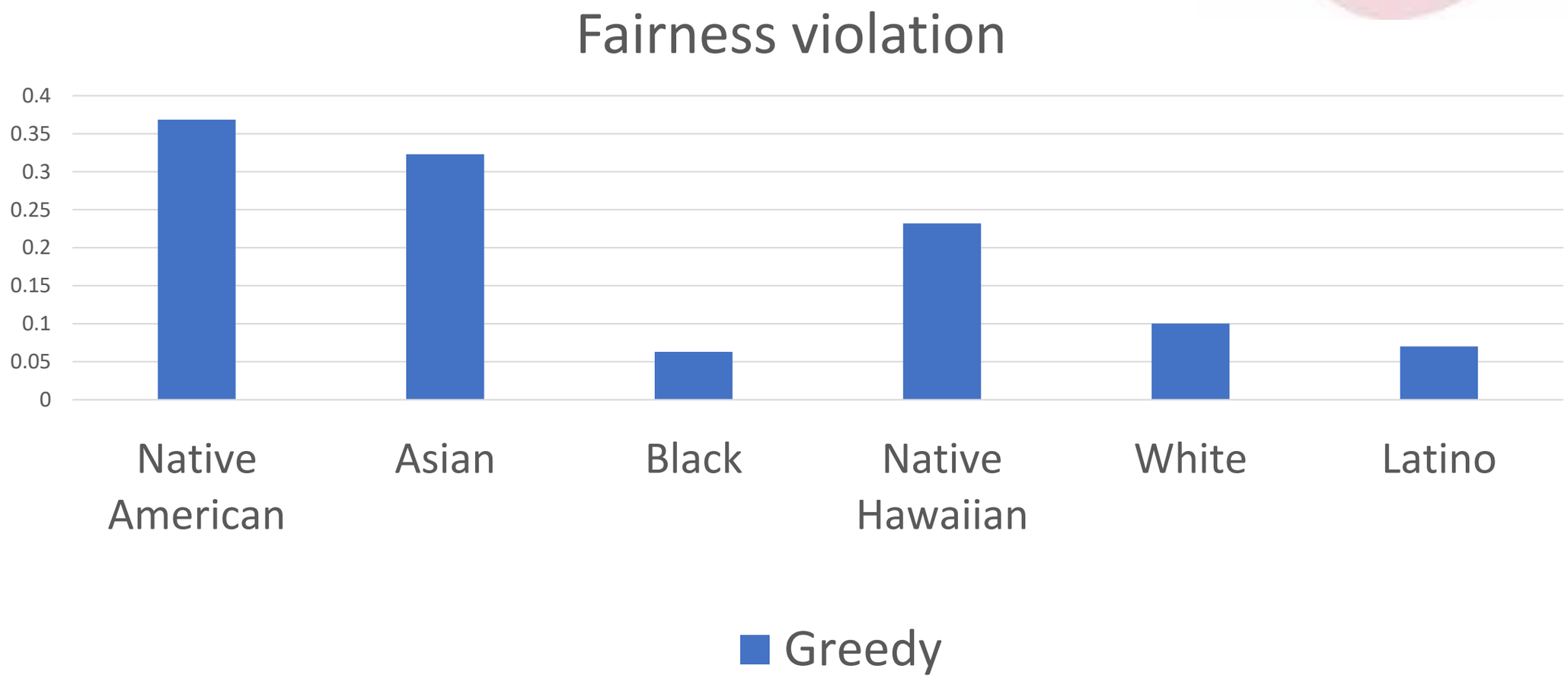
HIV Prevention in Marginalized Populations: Choose Peer Leaders *(IJCAI 2019)*

- Intervention: Influence maximization
- Are there any fairness violations?





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

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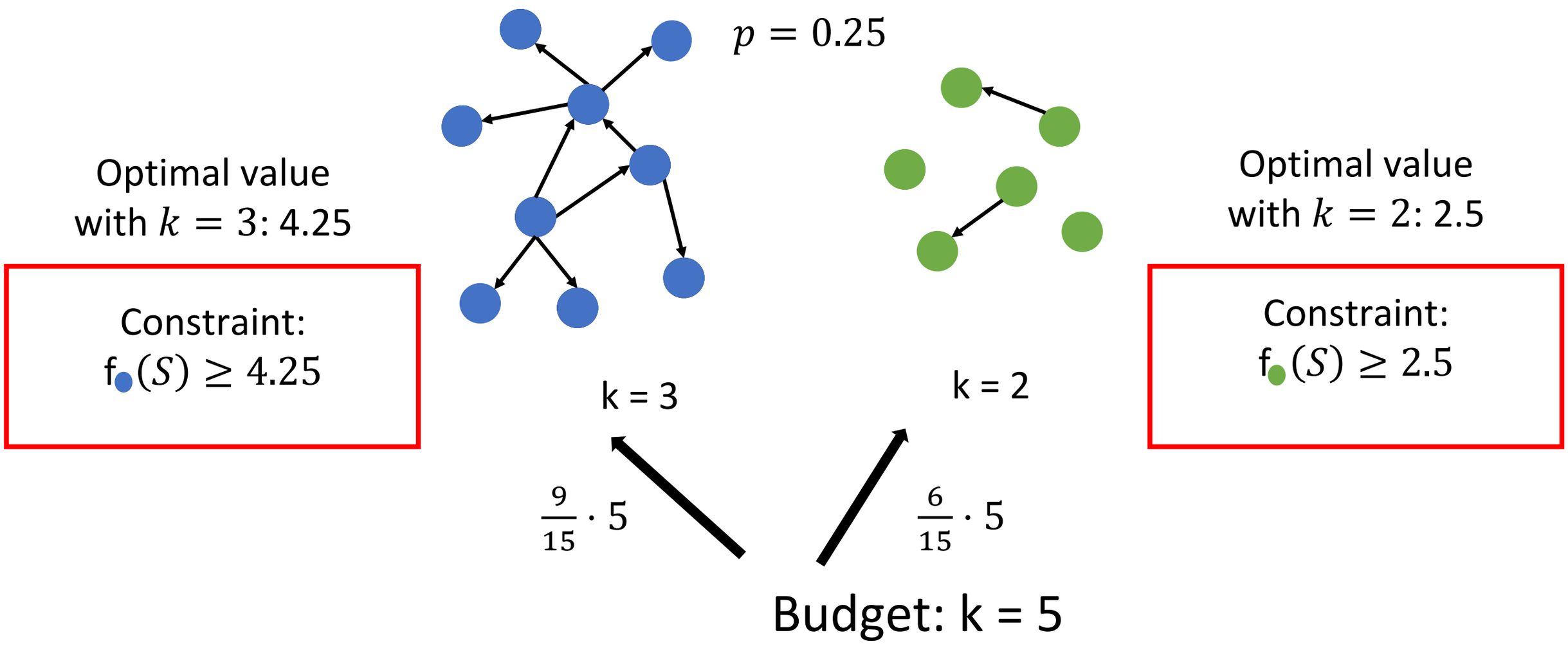
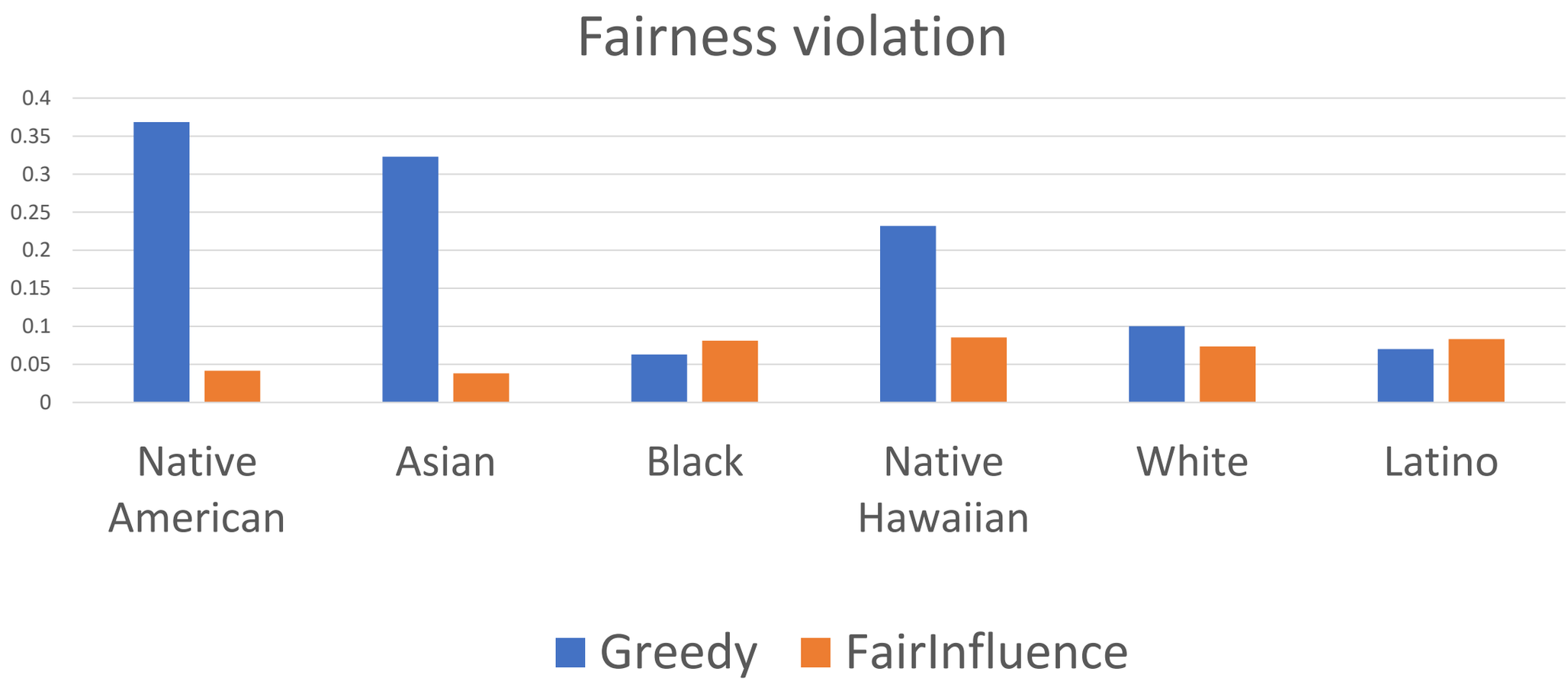


Multiobjective Influence Maximization Towards Addressing Fairness Challenges

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



Fairness in TB Treatment
AI & Multiagent Systems for Social Impact

- 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