AI and network intervention for HIV prevention

Milind Tambe

Harvard University
&
Google Research

Advancing AI/ML for Social Impact (AI4SI)

Public Health
Global Health

Conservation

Public Safety
and Security

Optimize Our Limited Intervention Resources

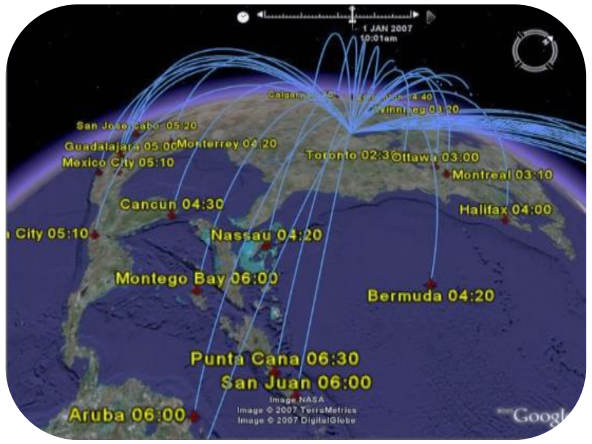
AI4SI Opportunities
Previous Work on Limited Resource Allocation

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

POLICE

Transportation Security Administration

Stackelberg security game



Wildlife Conservation Society

SMART

WWF

Air Shepherd
The Lindbergh Foundation

Green security game

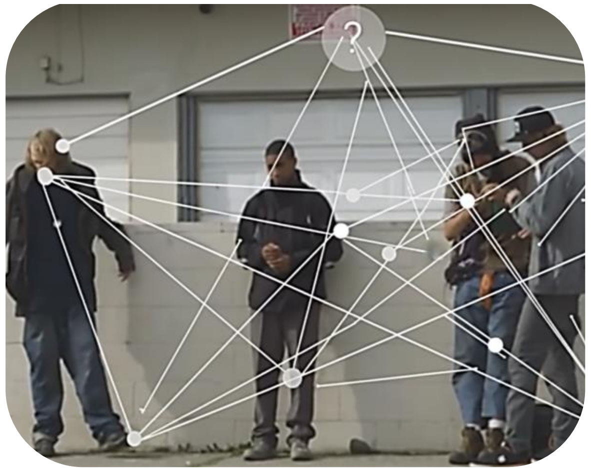
my friend's place

S.P.Y
safe place for youth

LOS ANGELES LGBT CENTER

armman
Delivering India's Future

Social networks & bandits



Outline: AI for HIV Prevention

- *Social network influence maximization for HIV prevention*
- *AI for network based HIV testing*
- *Addressing data limitations in HIV testing*
- *Addressing other public health challenges*
- *LLM Agents*

Harnessing Social Networks for HIV Prevention

With Prof. Eric Rice

Yadav

Youth experiencing homelessness: HIV/AIDS 10x housed population

Harnessing Social Networks for HIV Prevention

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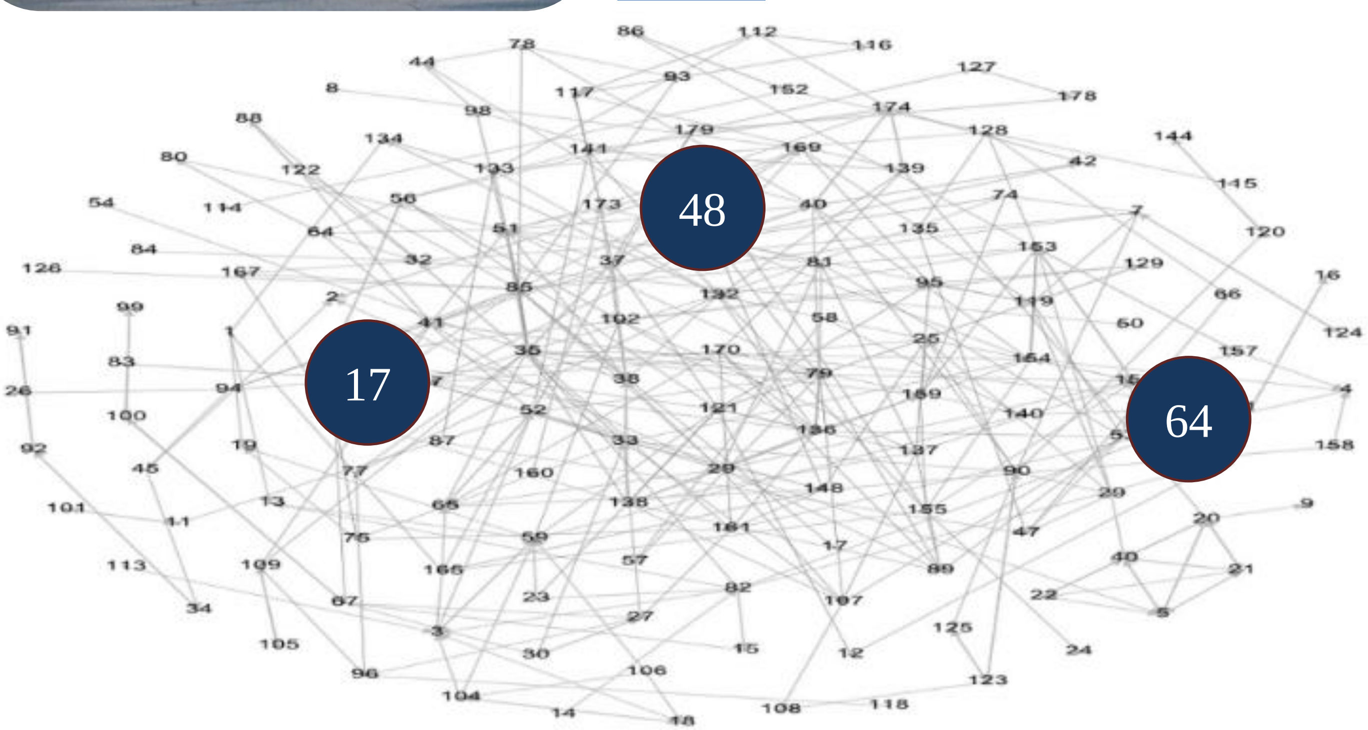
(IAAI 2015, AAMAS 2016)

Yadav

Youth experiencing homelessness: HIV/AIDS 10x housed population

- *Select small number of peer leaders to spread HIV information in social networks*



Data Gap: No Network

(AAAI 2021, Journal of AIDS/JAIDS 2021)

Wilder

Youth experiencing homelessness: HIV/AIDS 10x housed population

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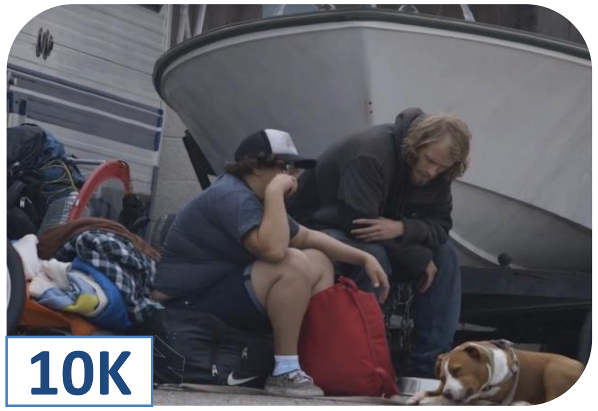

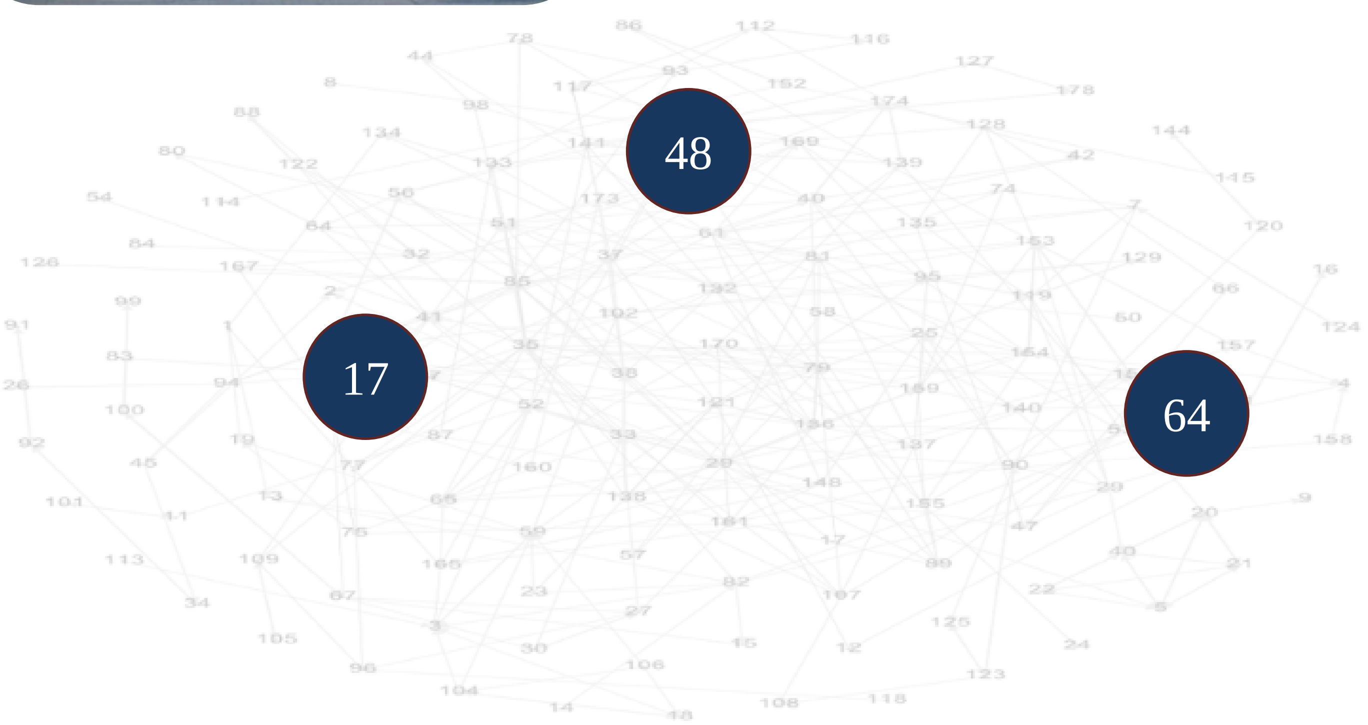

Observational Scarcity Gap: No Network

(AAAI 2021, Journal of AIDS/JAIDS 2021)

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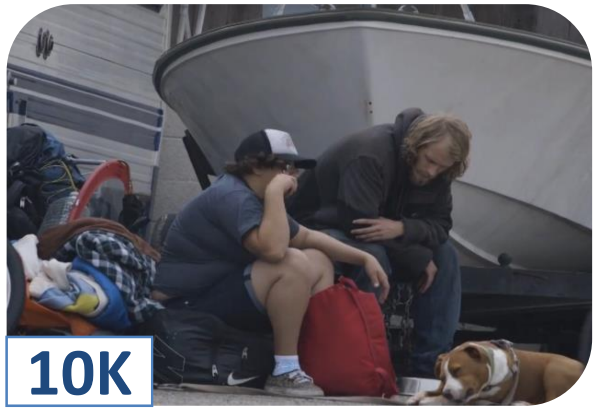
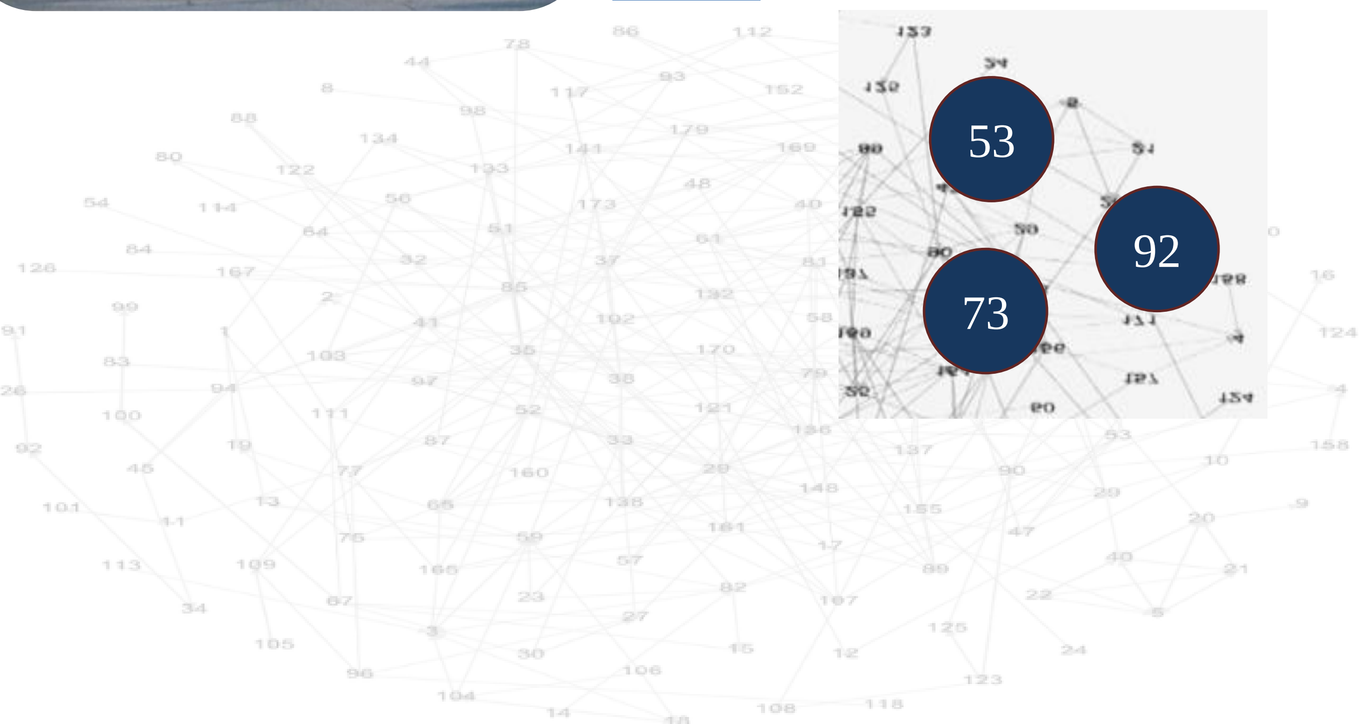




CHANGE

Network Sampling

↓

Robust multi-step policy

↓

Peer leader selection

Date: 3/3/2026

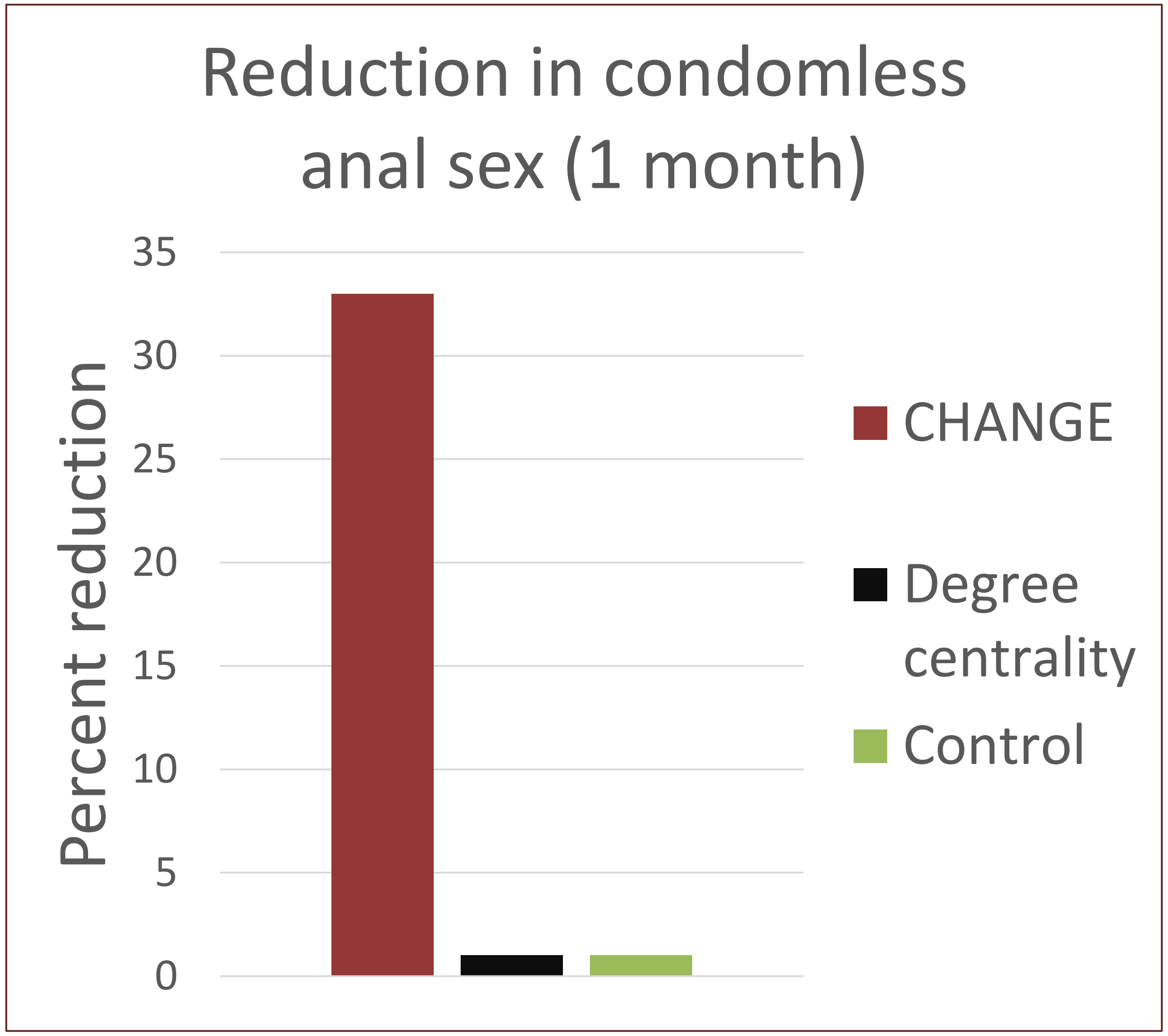
Results of 750 Youth Study [with Prof. Eric Rice]

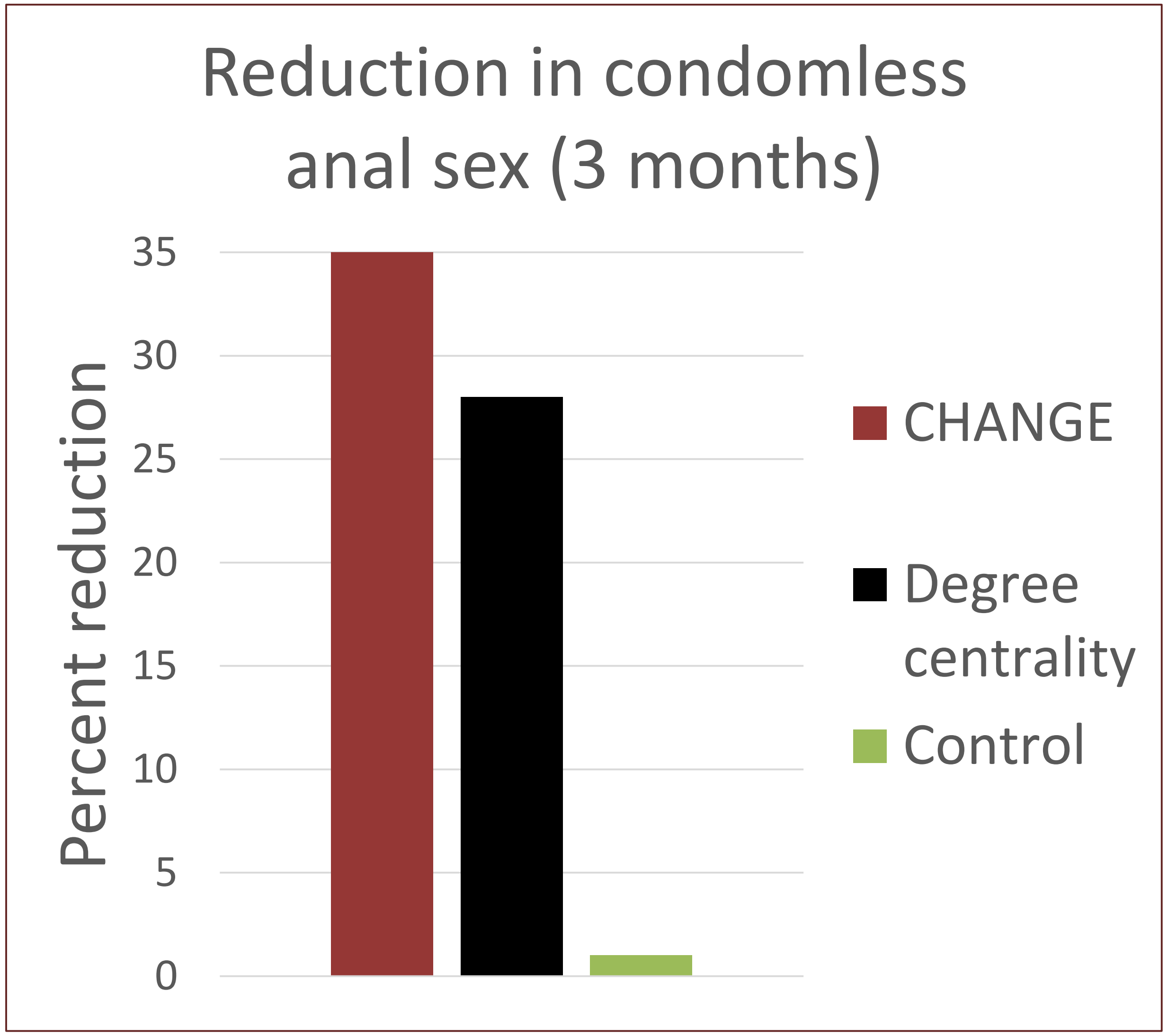
Wilder

Actual reduction in HIV RISK Behavior?

(AAAI 2021, Journal of AIDS/JAIDS 2021)

Change vs Degree centrality vs Control





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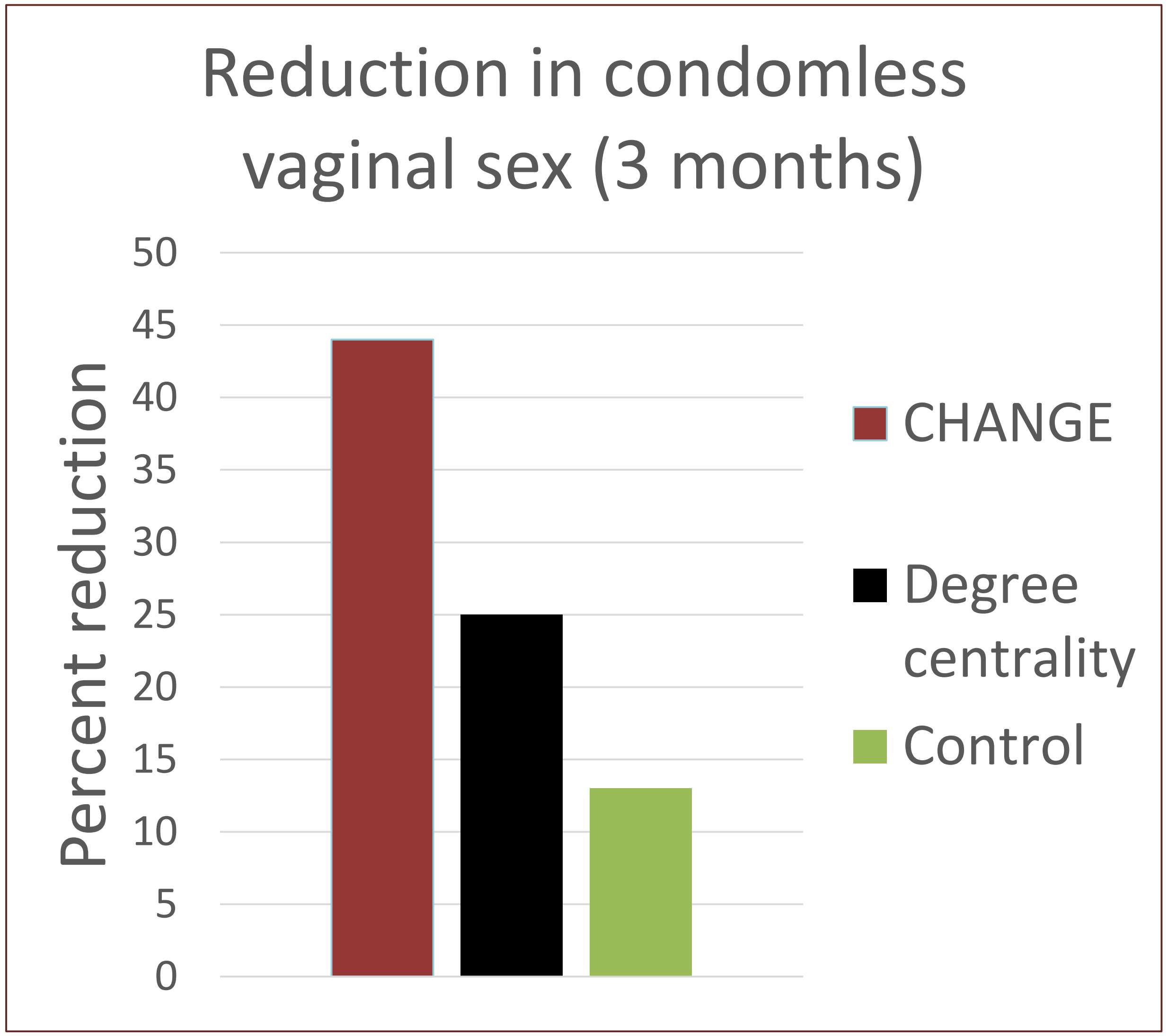

**Statistical significance results in AAAI’21, JAIDS’21*

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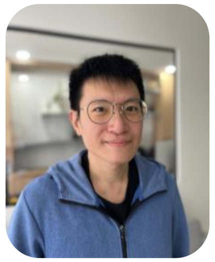
Network Based HIV testing
In collaboration with WHO, WITS


Choo


Pan

Estimated ~6 Million people worldwide do not know HIV status*

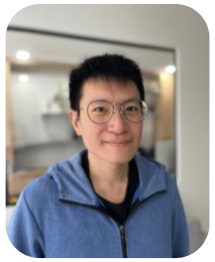
- Efficient testing to identify HIV+ individuals as early as possible:
  - Faster treatment for HIV+ individual
  - Contain further HIV spread

- **Key resource challenges: Number of HIV tests, health worker time**

*UNAIDS. Global HIV&AIDS statistics—fact sheet. 2024. Accessed August 30, 2024.
**https://www.icpsr.umich.edu/web/ICPSR/studies/22140/summary

New Challenge: Network Based HIV testing

In collaboration with WHO, WITS



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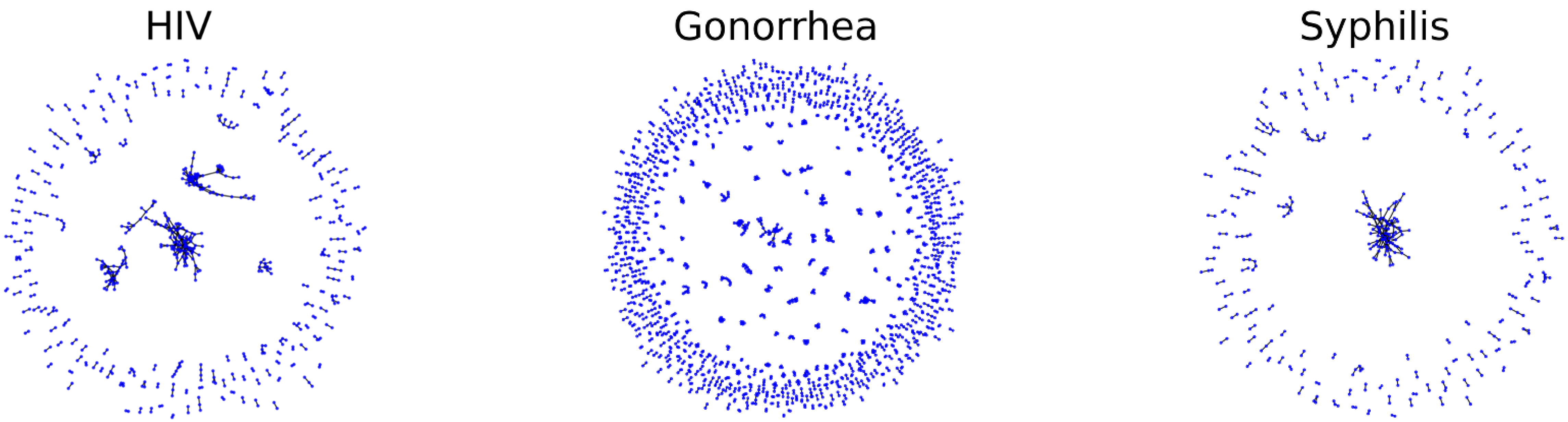
Estimated ~6 Million people worldwide do not know HIV status*

- **Key resource challenges: Number of HIV tests, health worker time**
- WHO recommends network based testing
- Key observation from real data: Sparse transmission networks**



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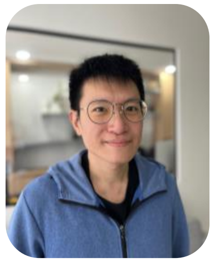
Network-based Disease Testing: Setup

(NeurIPS 2025)



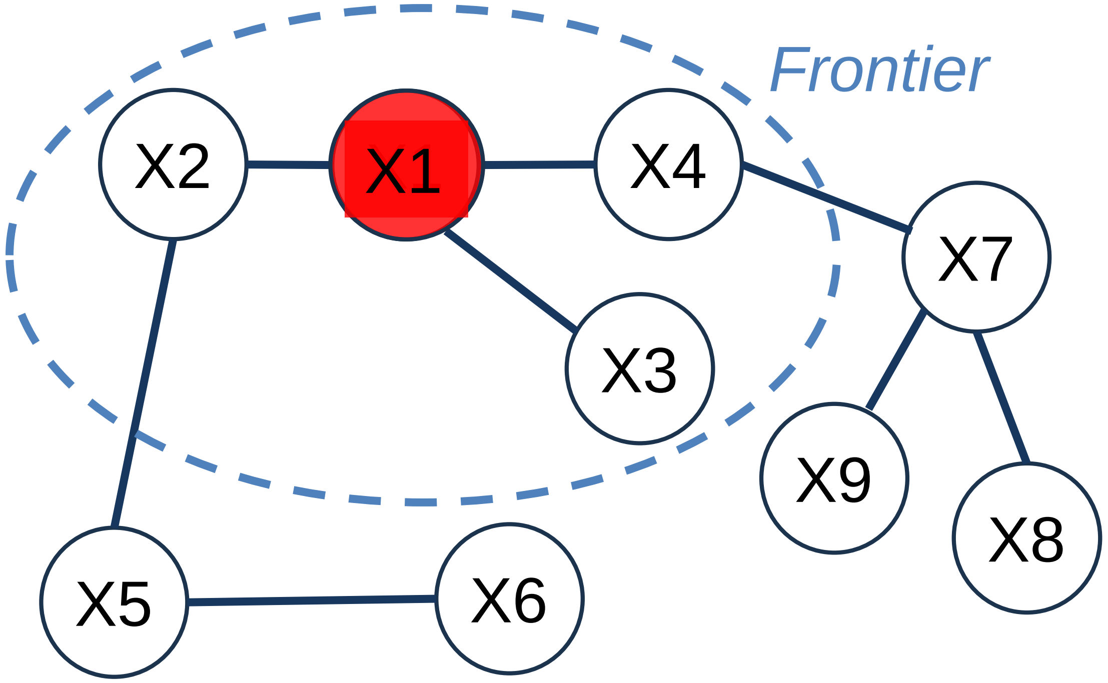
Choo

Pan

Assume: Given sparse HIV Transmission network (forest)

- Assume node features are given (e.g., age, marital status,…)
- Node features: Infer joint probability distribution of node status **(HIV + / –)**
- Markov property: Conditional independence of node status given neighbors
- Select nodes to test from frontier nodes

Policy: *Node testing sequence to maximize positive detections as early as possible?*



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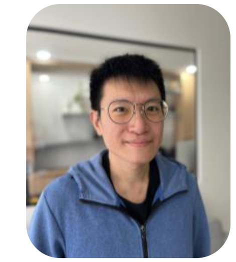
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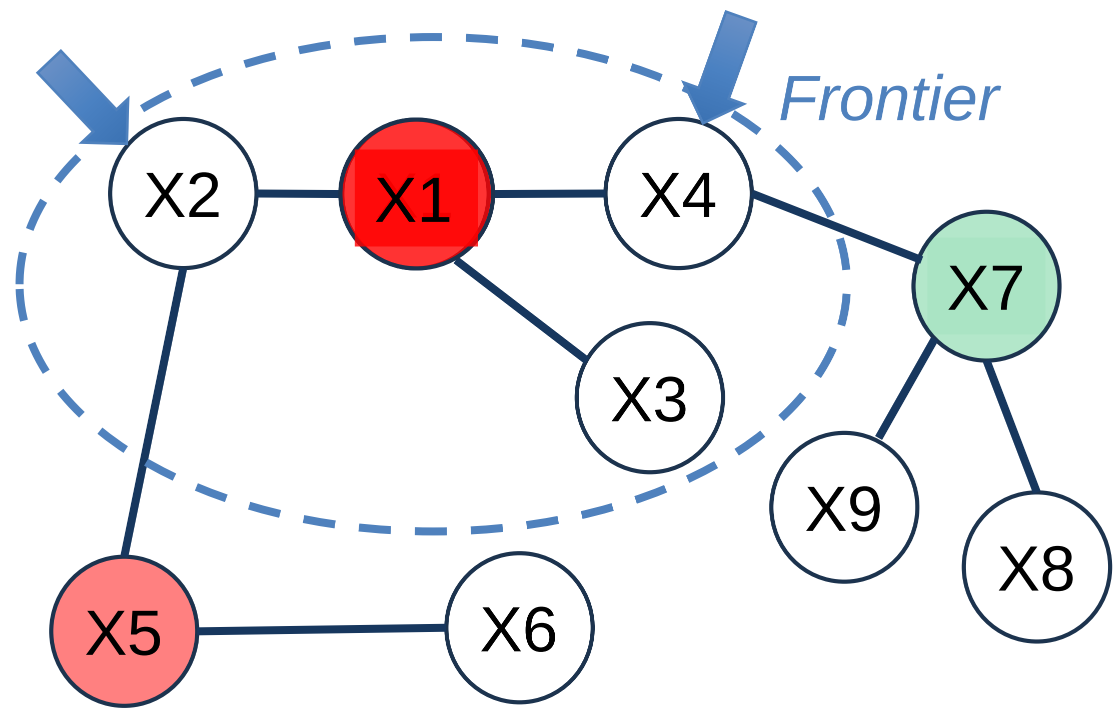
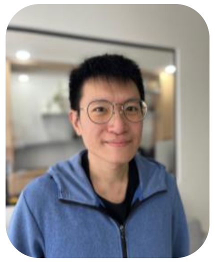
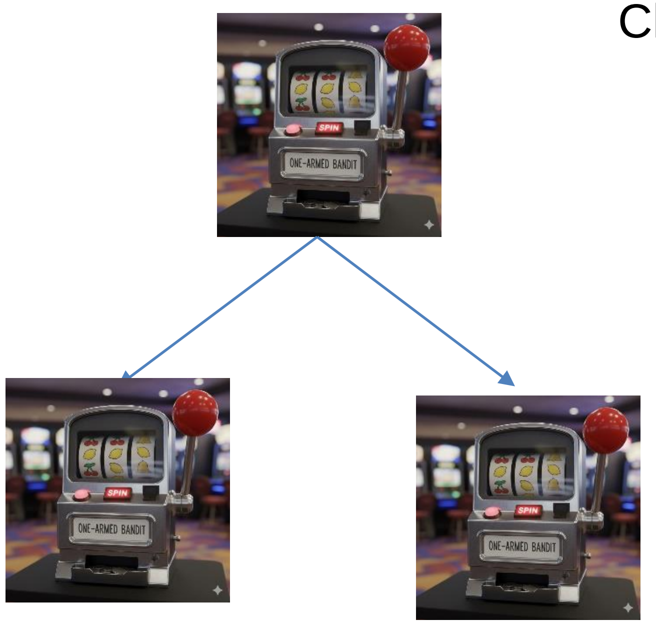


Network Based Testing:
Problem Maps to Branching bandits and Gittins index
(NeurIPS 2025)




Choo   Pan



Forest network testing maps to *branching bandits*:

- Pulling an arm gives rewards and new arms
- Our case: Testing one node reveals frontiers nodes

- Branching bandits: Gittins index optimal (Keller & Oldale 2003)
- Our contribution: Fast computation of Gittins by showing piecewise linearity in m

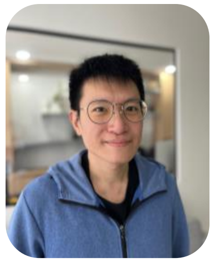
$$\mathrm{G}ittins(\text{Node}\, X, b) = \min\{m : \phi_{X,b}(m) \geq m\}$$

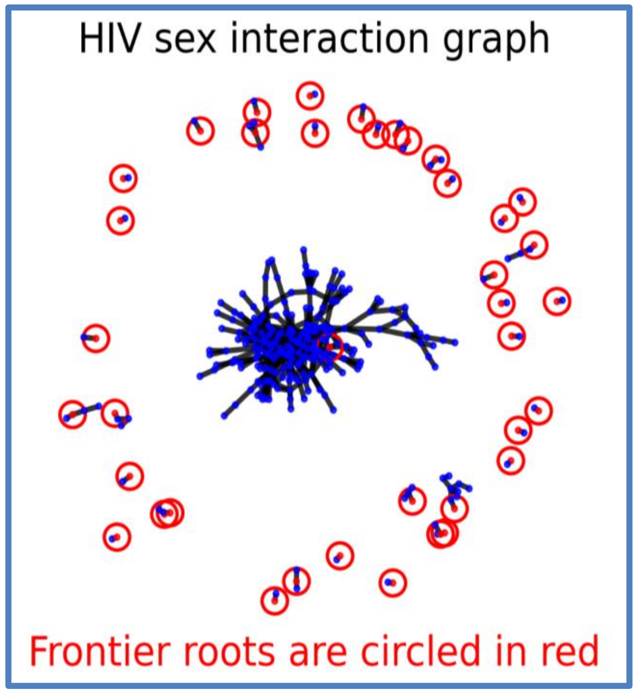
Parent(X) value b (1 or 0)
m: Stopping value

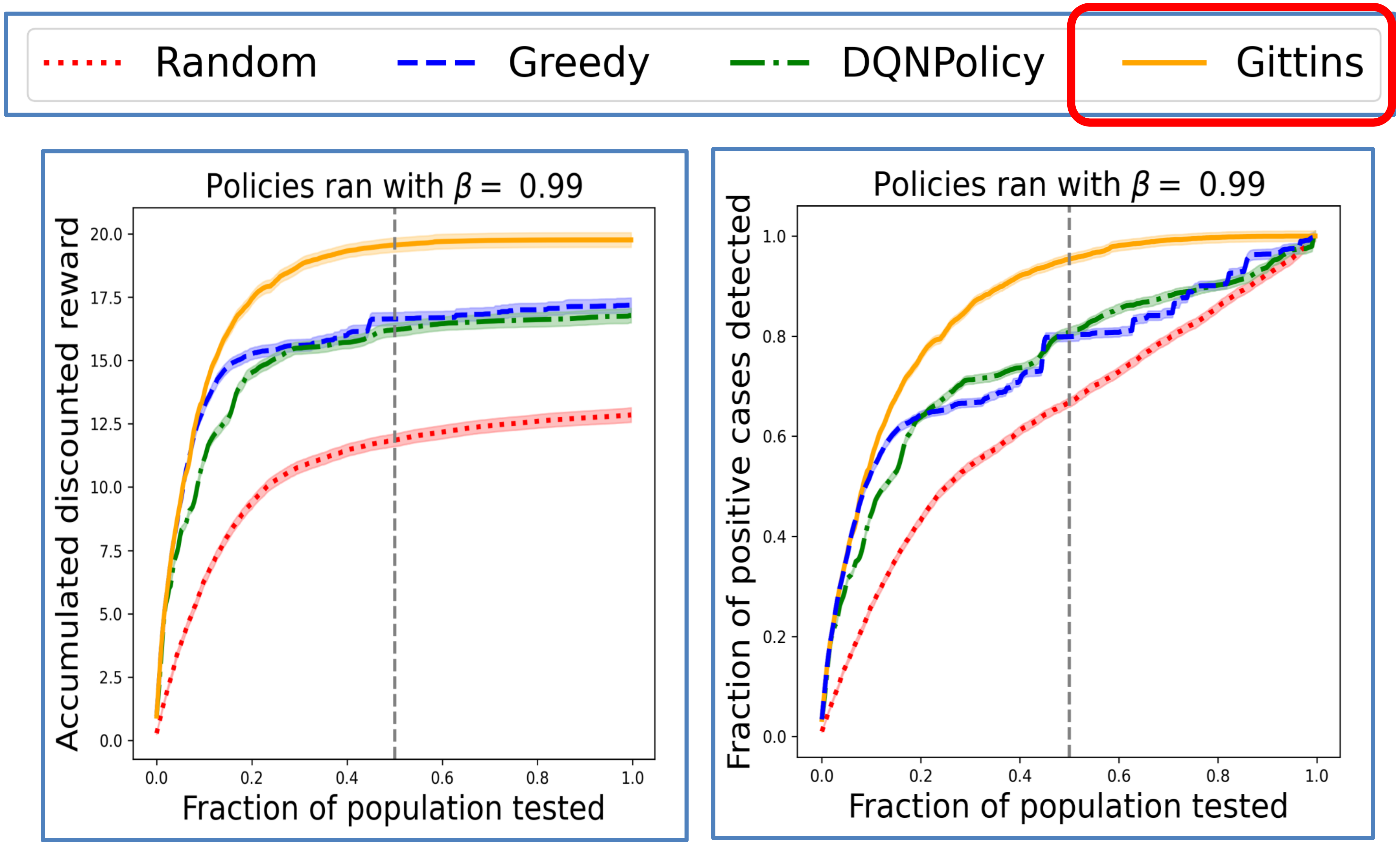
[KO03] Godfrey Keller and Alison Oldale. Branching bandits: a sequential search process with correlated pay-offs. Journal of Economic Theory, 113(2):302–315, 2003.

Simulation results

(NeurIPS 2025)







Discounted **Undiscounted**

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Kangaslahti

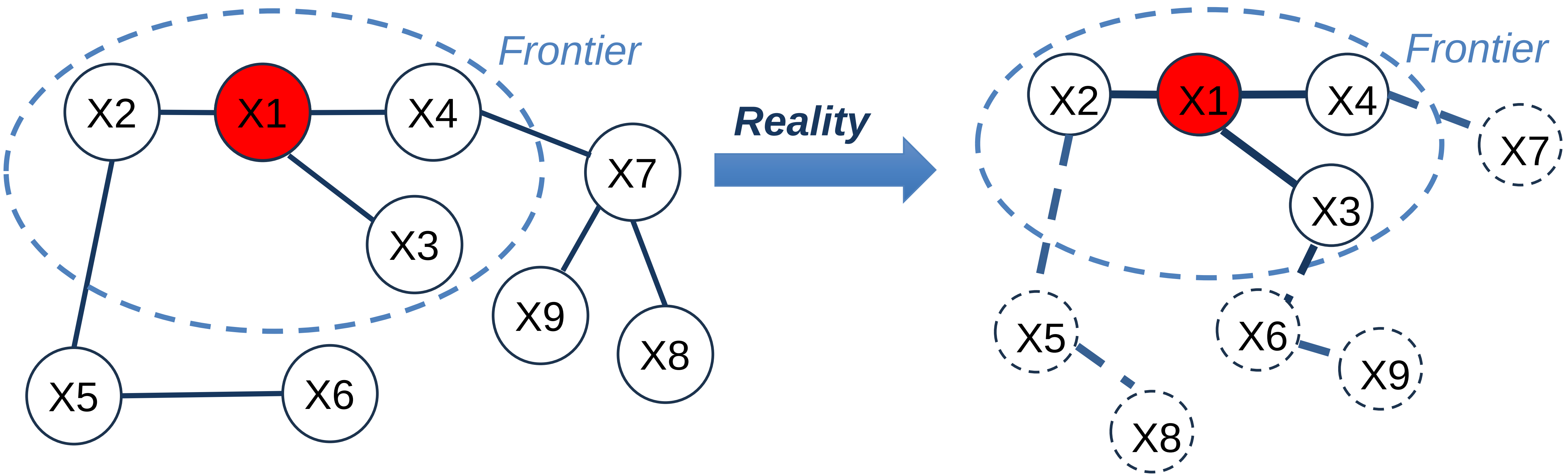
Observational Scarcity Gap

Predict Graph Expansion

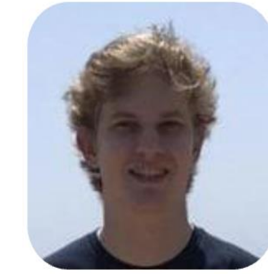
Key novelty: "Policy embedded" graph expansion

- Focused on HIV testing optimization, not on topological accuracy
- Iterate: Select highest Gittins index node in frontier, then expand

Assumed Full Knowledge ***Predict Graph Expansion ?***

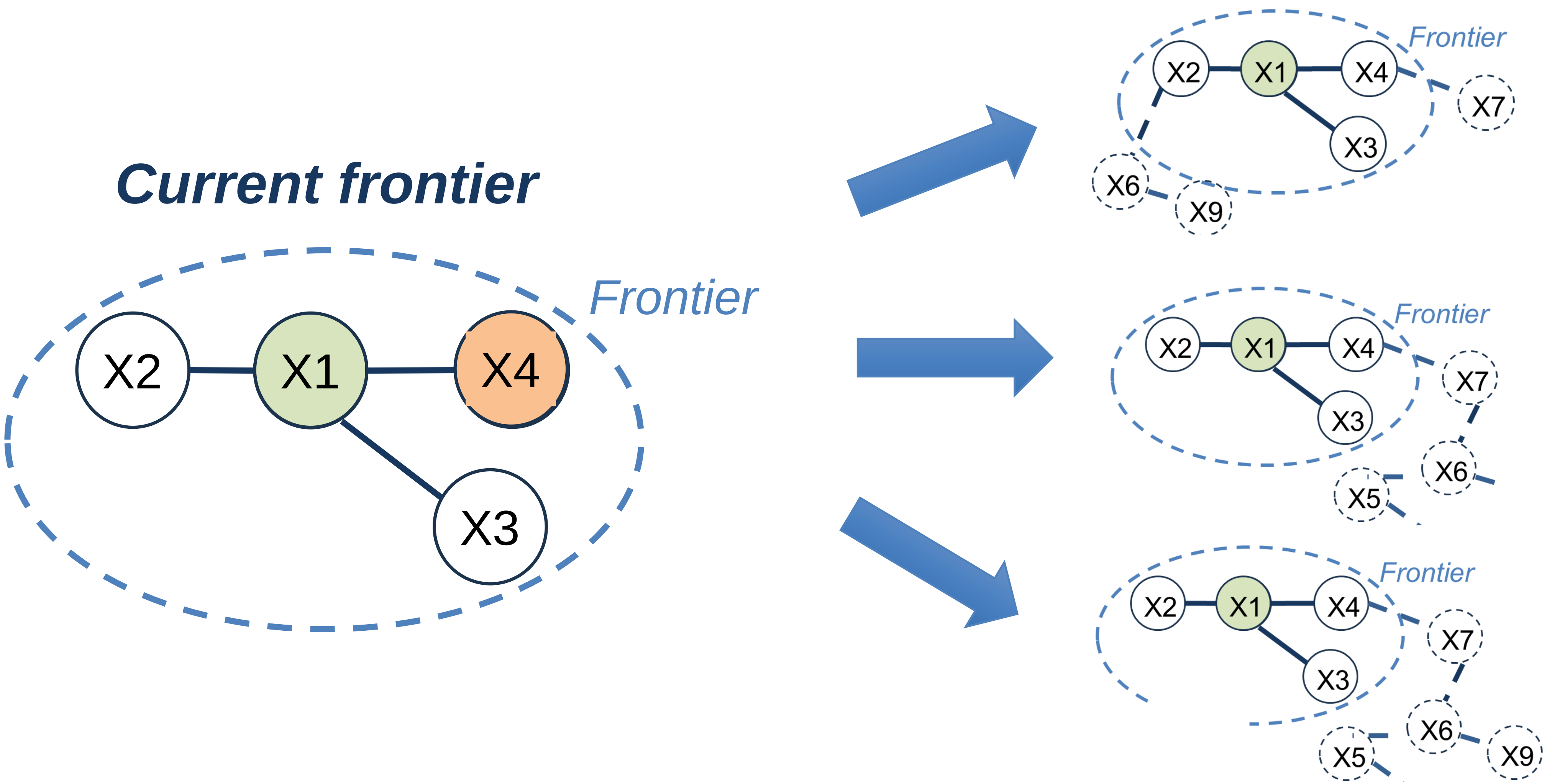


Diffusion Models as Data Generators
Generate Distribution of Partial Graph Expansions


Kangaslahti

Diffusion models: At each step, generate graph variants with key node features

- Handles high dimensionality of node features in variants *(age, marital status, drug use…)*
- Select frontier node with highest average Gittins index given expansions



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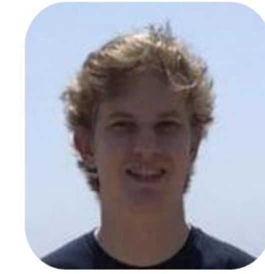
Kangaslahti

Diffusion models: At each step, generate graph variants with key node features

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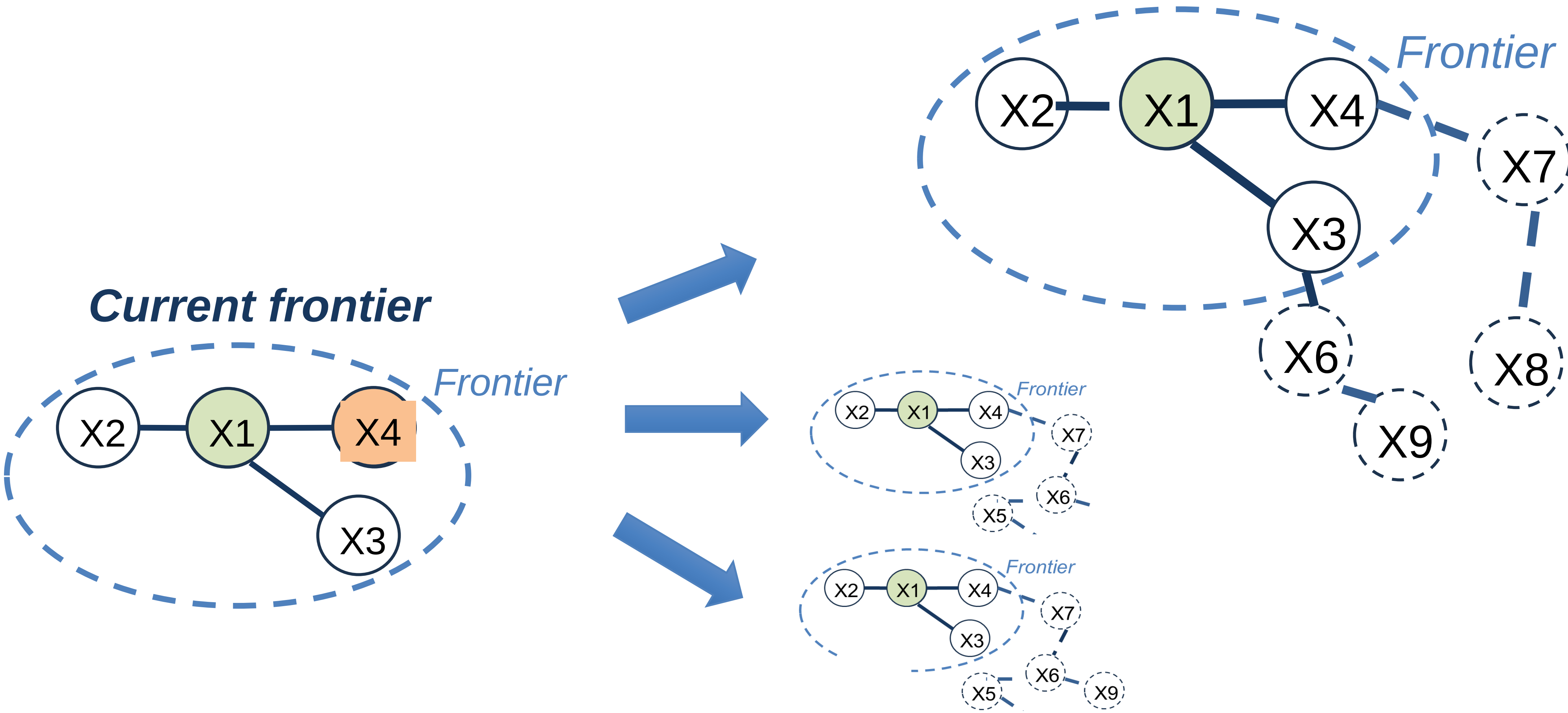
Challenge is limited training data: Address by exploiting forest structure

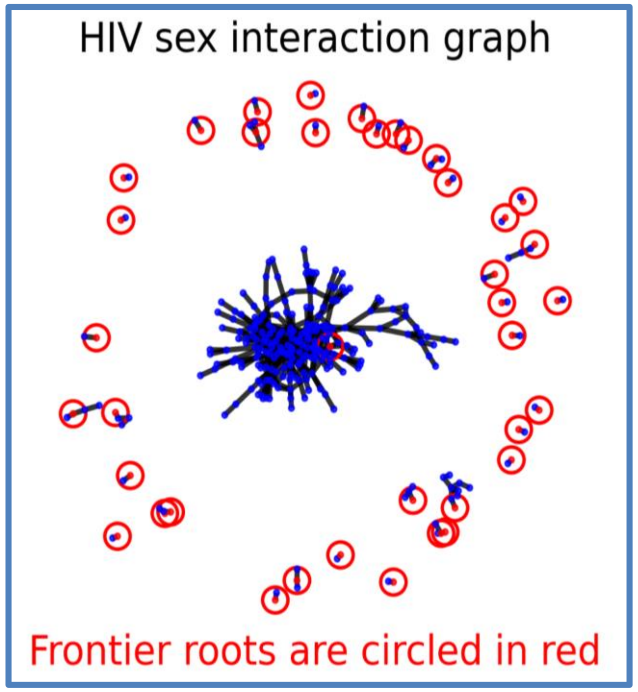
- Edgewise auto-regressive diffusion, not generate full graph all at once
- Variance due to focus on node-to-node relations

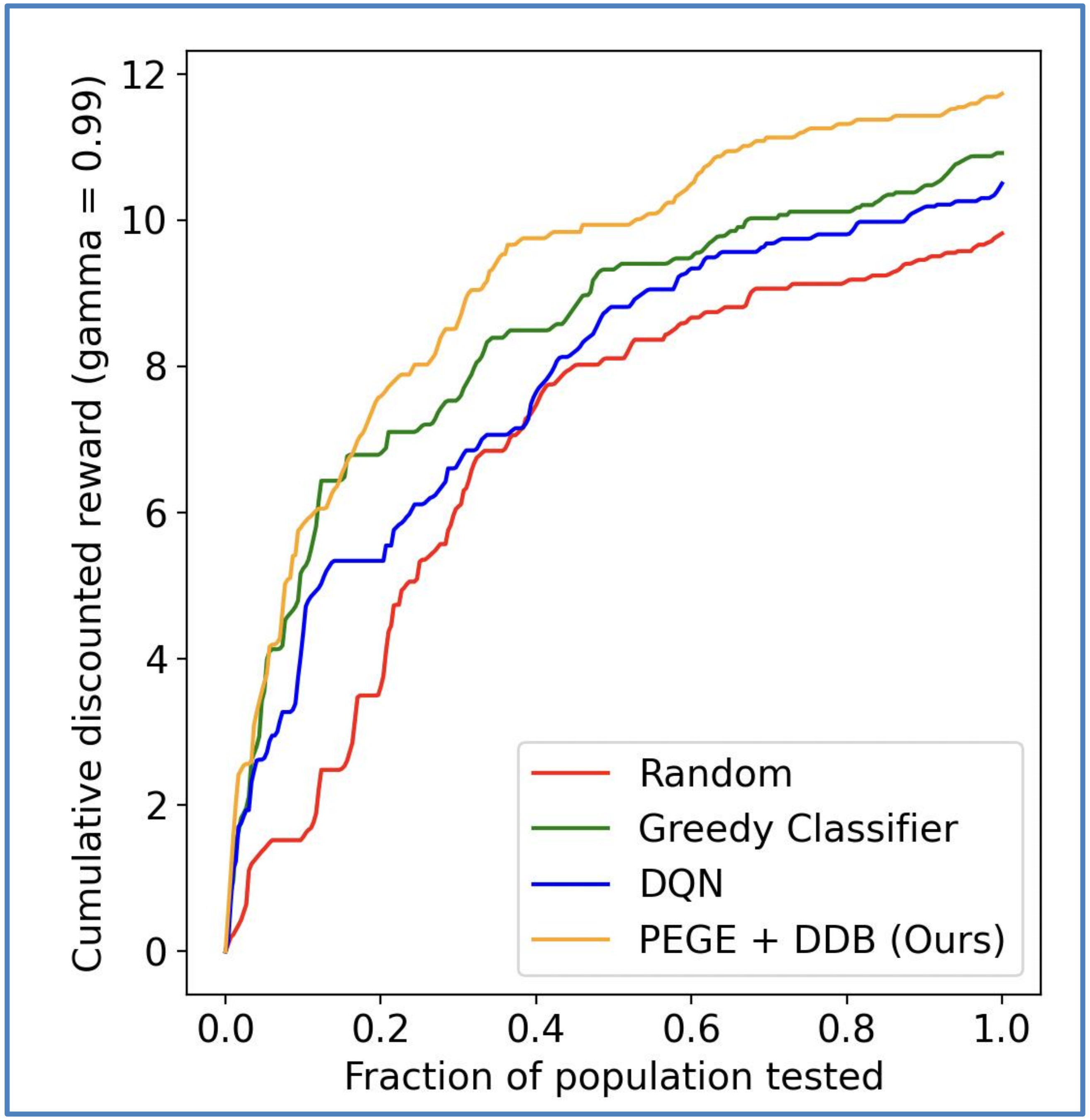


Simulation Results

(Under submission)

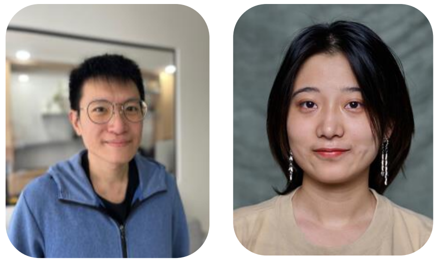
Kangaslahti





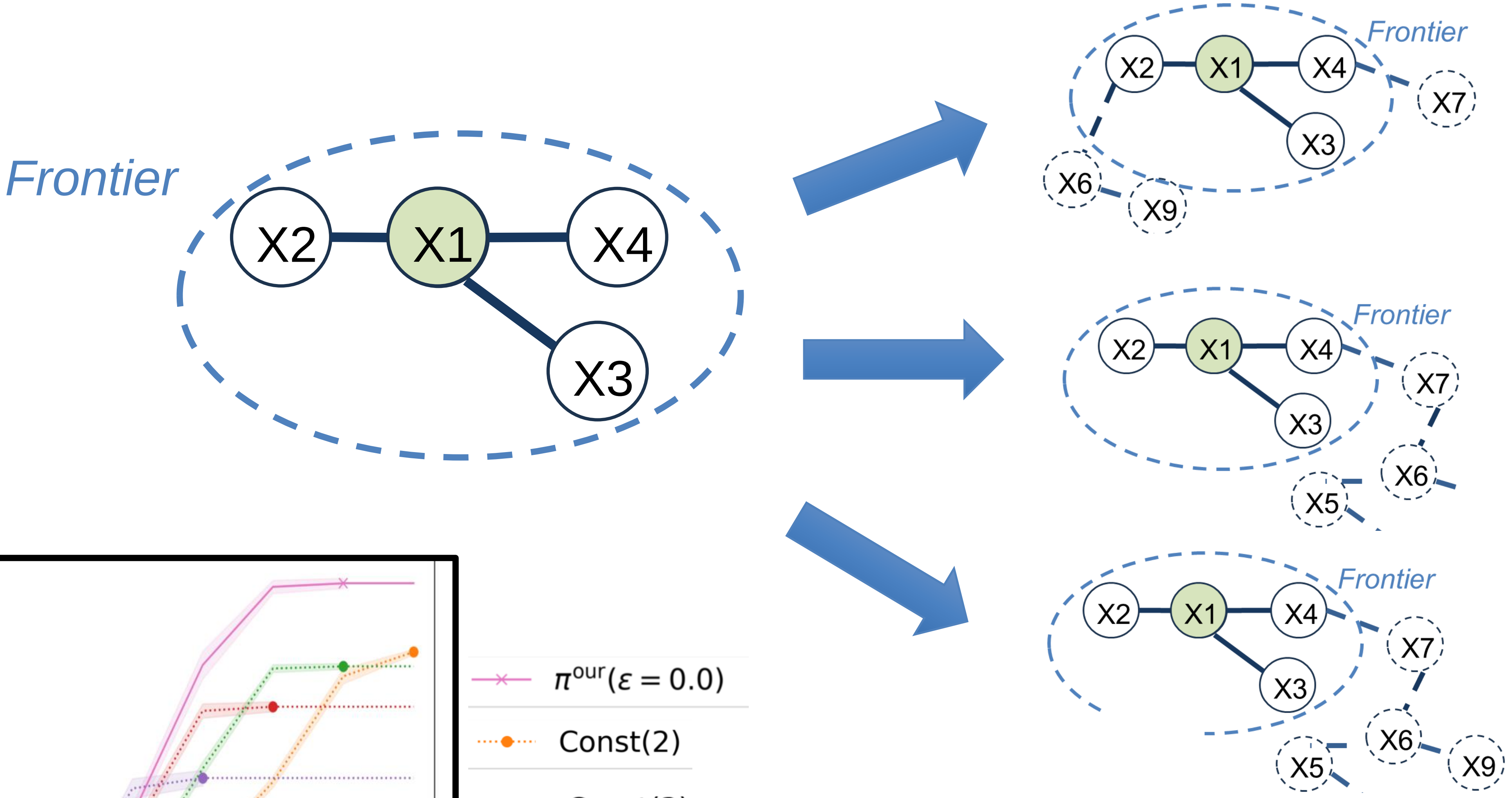
Another Approach to Testing

(Under submission)

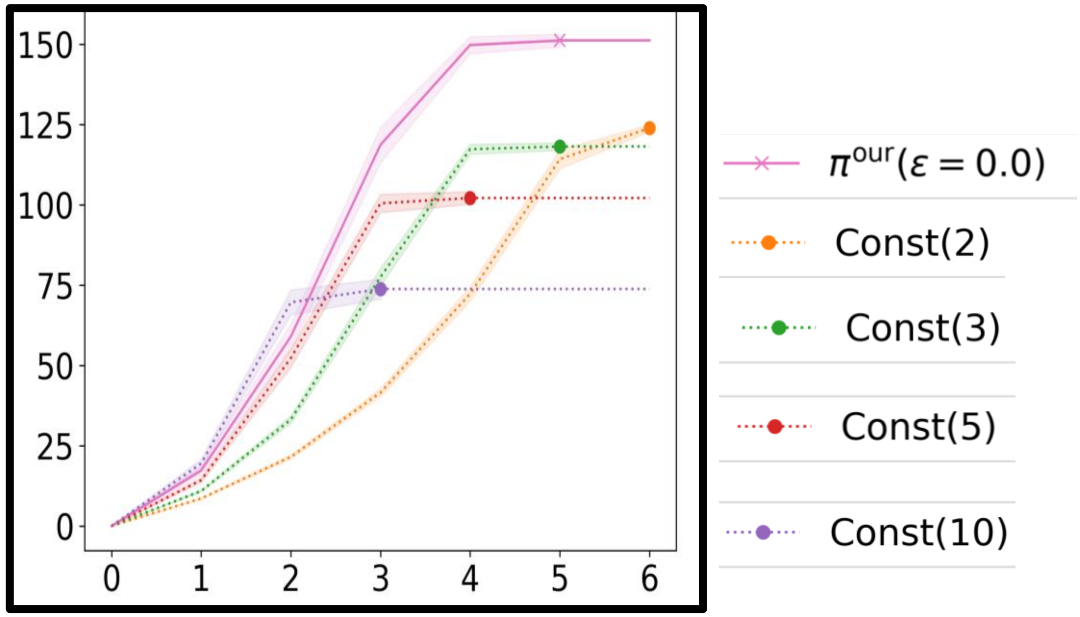


How many self test kits to hand out to different frontier nodes?

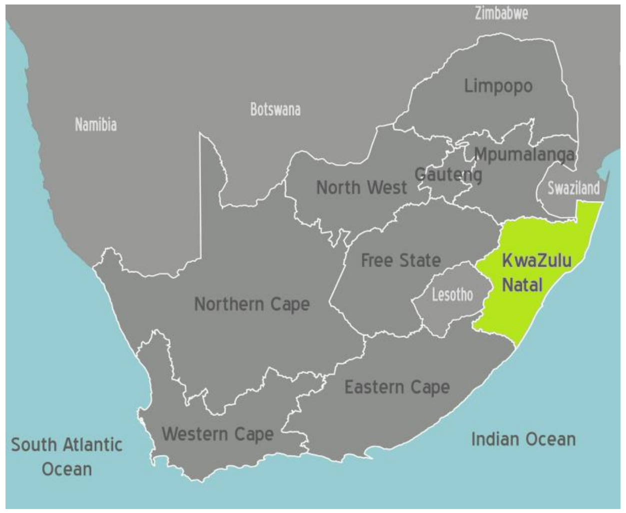
- Current approach: Identical number of kits to each node
- New approach: Different numbers of kits based on recruiting ability



Discounted reward: Num of individuals with self test kits



Towards a trial and deployment



- Trial in KwaZulu-Natal South Africa

Prof. Alastair van Heerden

Cheryl Johnson

World Health Organization

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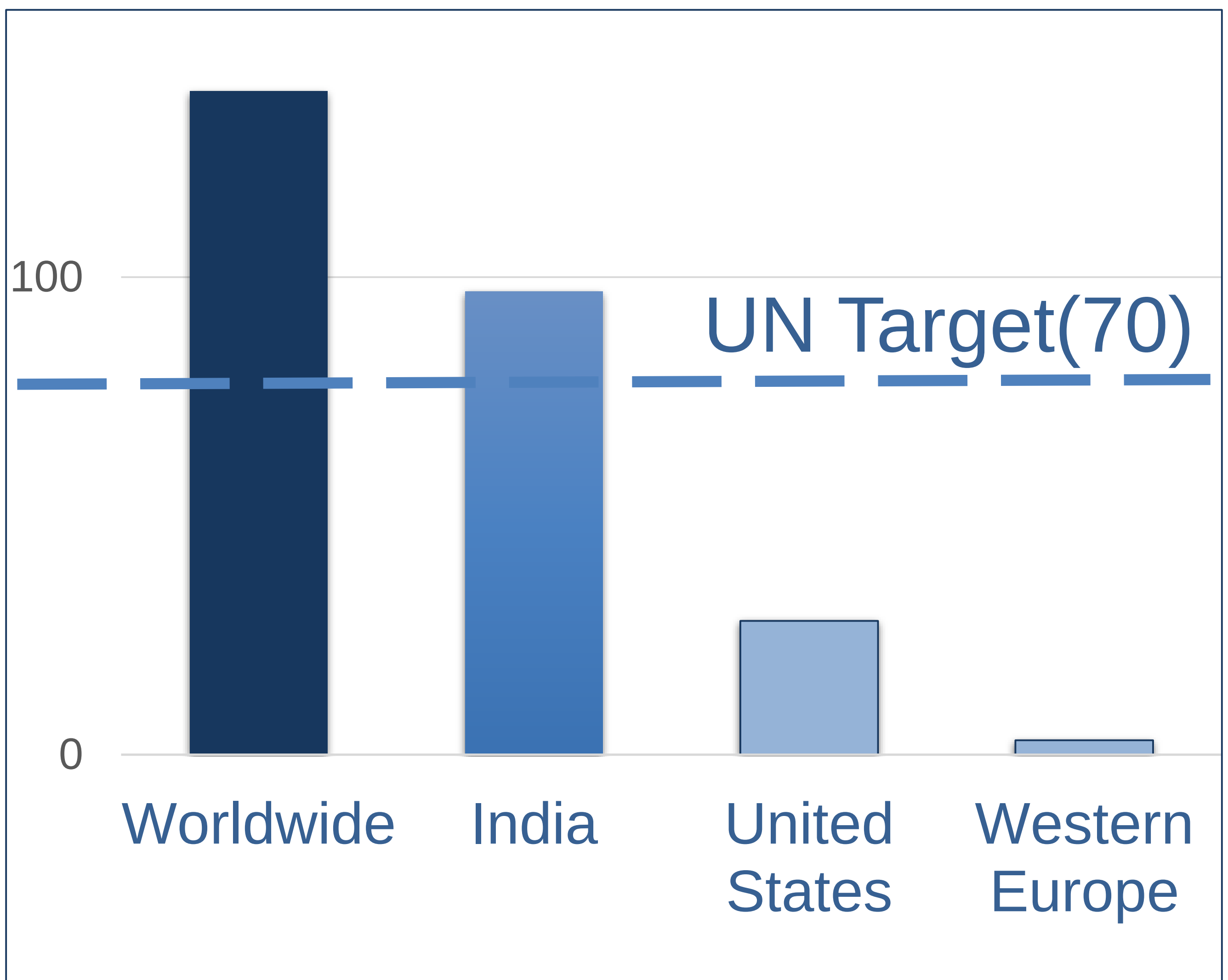
Maternal Health Crisis

UN SDG (2030): Maternal mortality ratio below 70 per 100,000 live births

Maternal Mortality Ratios (2023)



ARMMAN
DELIVERING INDIA'S FUTURE

Credit:https://www.gatesfoundation.org/goalkeepers/report/2024-report/#maternal-mortality

ARMMAN's mMitra Mobile Health Program: For new/expecting mother

- *Weekly 2 minute automated health messages*
- ***141 voice messages***
- *Over 3.6 million women have benefited*

mMitra *(snippet of audio message)*

For you and your baby to be strong,
you need lots of iron. Iron-rich foods include
meat, jaggery and leafy green vegetables.

ARMMAN's mMitra Mobile Health Program: For new/expecting mother

- *Weekly 2 minute automated health messages*
- ***141 voice messages***
- *Over 3.6 million women have benefited*

Unfortunately, 40% beneficiaries may become low-listeners

30% increase in infants with tripled birth weight at end of year

29% increase in women who had more than 4 ANC visits

Intervention Scheduling with Limited Resources: Preventing 40% drop-offs

- *Large number N beneficiaries: 200000*
- *Automated health messages to all N each week*
- *Choose K=1000 for live service call per week?*
- *Maximize health messages listened to*

Beneficiary state: Dynamic, changing

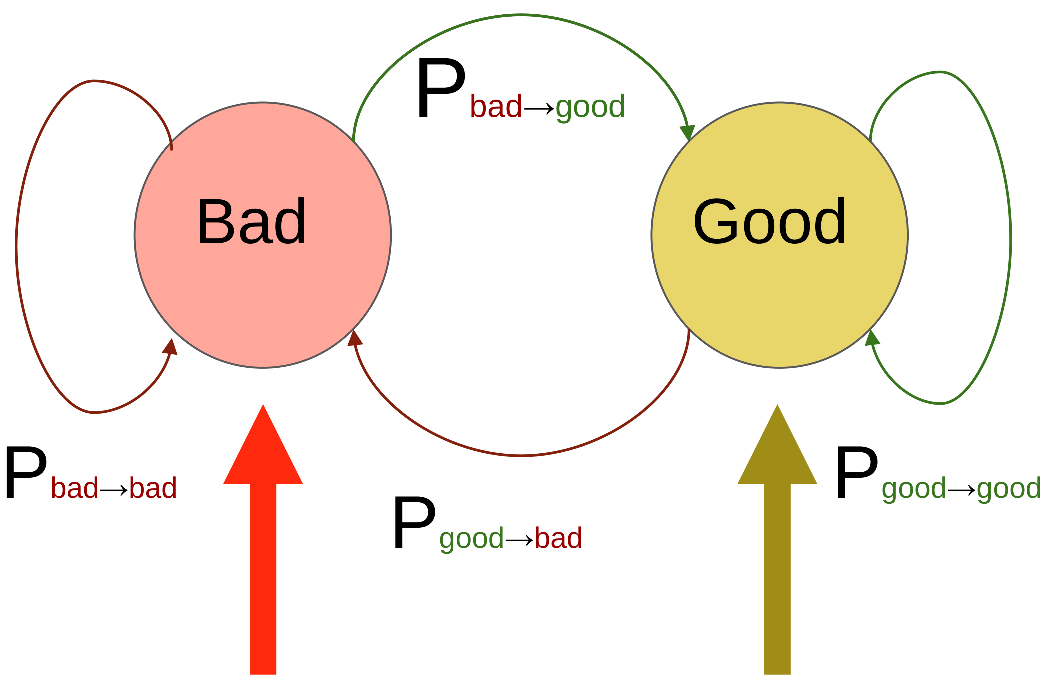
Restless bandits: Prioritize K of N beneficiaries with dynamic state

Restless Bandits: Each Mother modeled via an MDP (Markov Decision Problem)

Mate

States of MDP

“bad” state & “good” state



Reward 0

Reward +1

Actions

Intervene via service call

or

Not intervene

Transition matrix

Not intervene:

	Bad	Good
Bad	0.8	0.2
Good	0.2	0.8

Intervene via service call:

	Bad	Good
Bad	0.2	0.8
Good	0.05	0.95

Restless Bandits Model
Whittle Index: Efficiently Select K out of N Beneficiaries
(AAAI 2022)

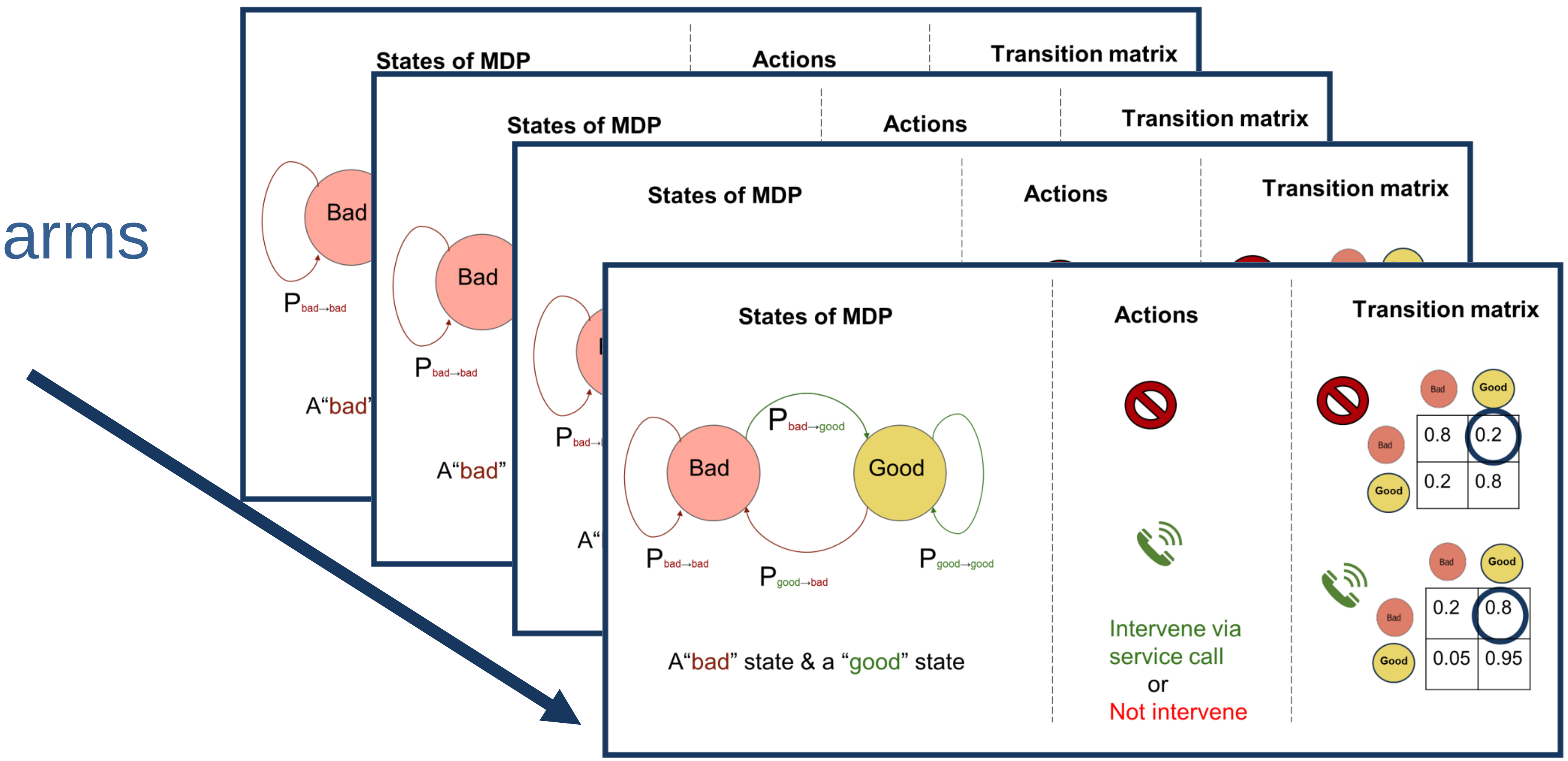

Mate

N-choose-K policy to maximize beneficiaries in "Good" state? *"Good" ➔ Reward*

Compute Whittle index for current state of each arm, i.e., benefit of intervention on arm

$W(s) = INF_{\gamma}\{\gamma\colon Q_{\gamma}(s,$  $) = Q_{\gamma}(s,$  $)\}$

From 200000 arms
Choose 1000

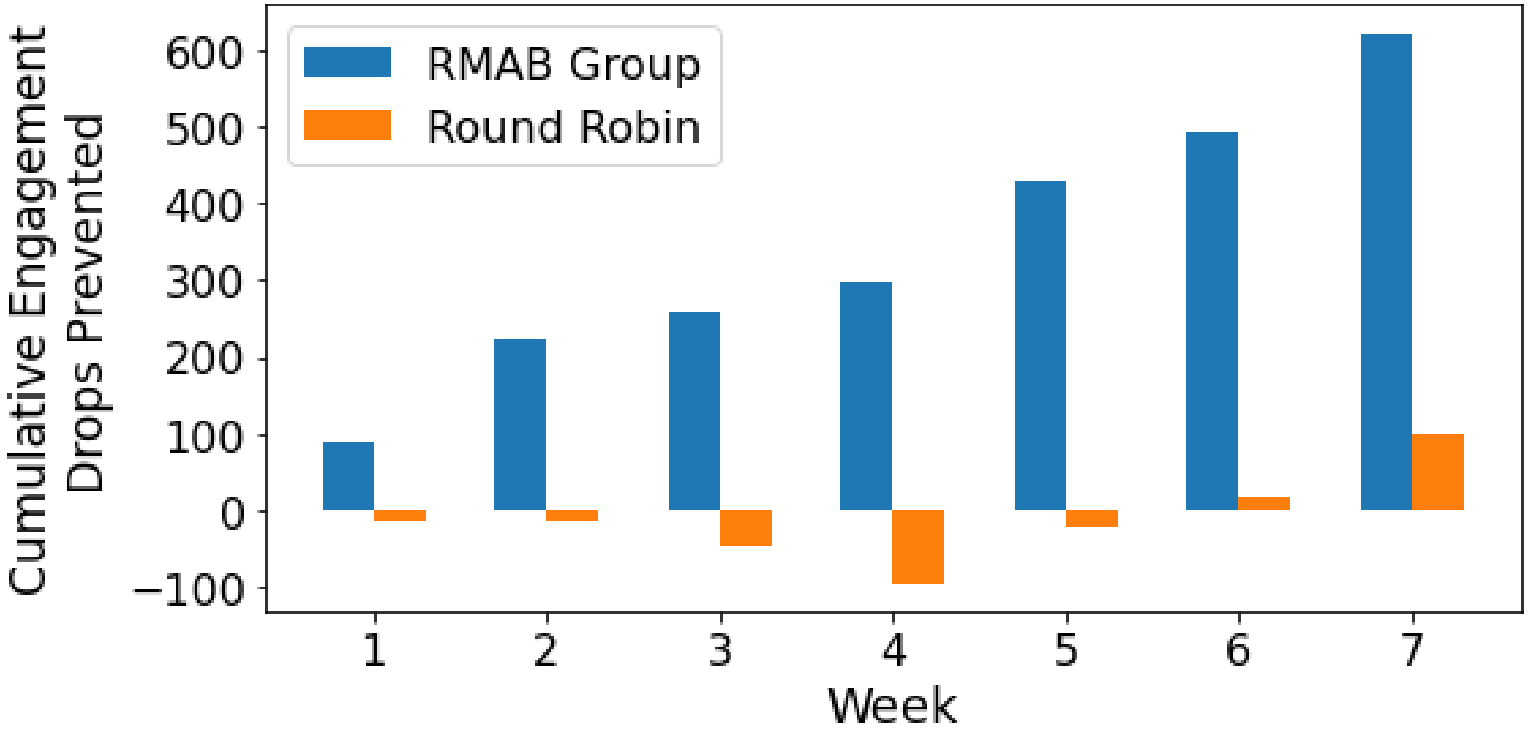


Results of 23000 Beneficiary Field Study

(AAAI 2022,2023,2025, ICML 2023, AAMAS 2023)

Mate

- 7667 beneficiaries per group: Restless bandits (RMAB), Round-robin, Current-Standard-of-Care
- All beneficiaries get automated health messages each week
- Pulled 225 arms/week for seven weeks (225 live service calls per week)
- How many more health messages listened to over Current-Std-of-Care
- **Restless bandits (RMAB) optimize service calls**



RMAB cuts drop off rate: 32%

Restless Bandits + DFL: Deployed at ARMMAN

(IAAI 2023, AI Magazine 2023)

Verma

- Deployed: **April 2022**
- Number of beneficiaries served: **350,000+**
- Drop-offs prevented: **30%**
- Bottom 25 percentile, content exposure increase: **130%**

Health Impact Study
(PAIS/ECAI 2025)


Dasgupta

- RMAB → higher listenership → Improved health behaviors:
  - *21871 beneficiaries*
  - *Matched intervention vs control*

Question	Percentage improvement	p value
Taking calcium tablets after delivery	24.4%	*p=0.04*
Taking iron tablets after delivery	18%	*p=0.09*
What was the baby's weight at birth?	9.2%	*p=0.01*

- Ultimately, AI intervention is improving health behaviors!

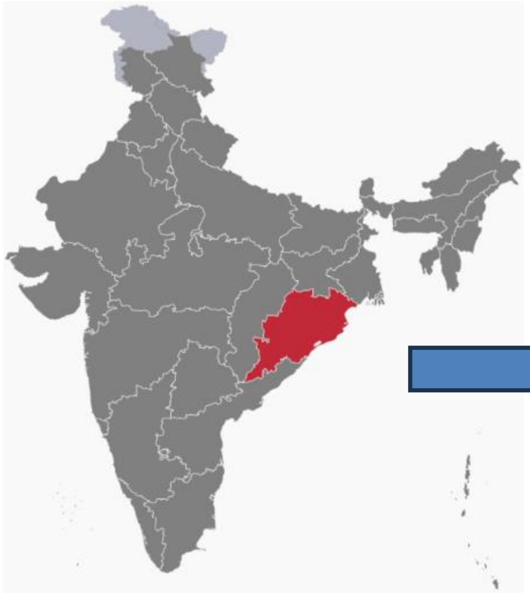
Kilkari: *World's Largest Mobile Maternal Health Program*

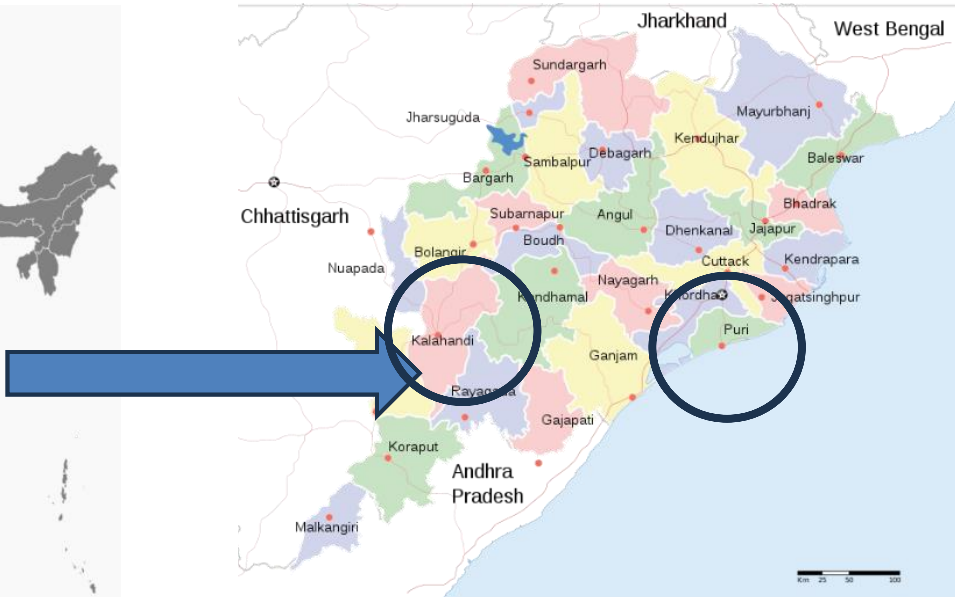
(IAAI 2024, MLHC 2025)


Dasgupta

Applied collaborative bandit algorithms to improve listenership

- *Govt of India program: Managed by ARMMAN*
- *3.5 Million mothers enrolled at a time; like mMitra*





Study in Kalahandi & Puri

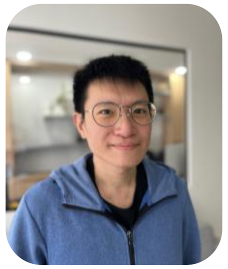
- Control vs Treatment groups
- 6400 beneficiaries per group

<u>12% increase in call listenership</u>

Date: 3/3/2026

AI for Maternal and Child Health

(IJCAI 2022, AAAI 2024, AAAI 2026)



Choo

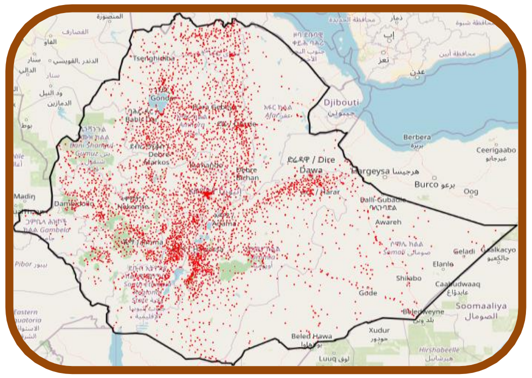
Trabelsi

Helpmum, Nigeria

Optimizing vaccination interventions (IJCAI'22, AAAI'24)

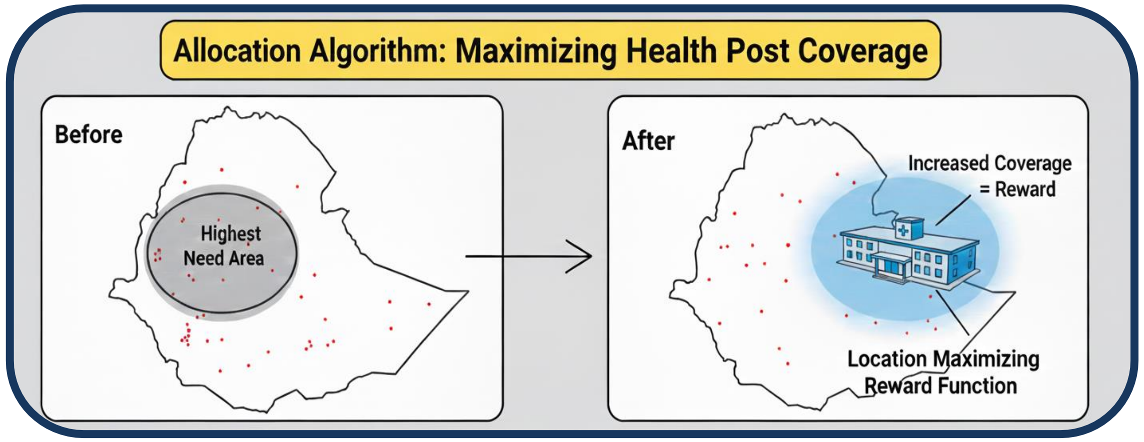
Deployed: 99 community centers in Oyo, Nigeria, with 13K beneficiaries

Ministry of Health, Ethiopia



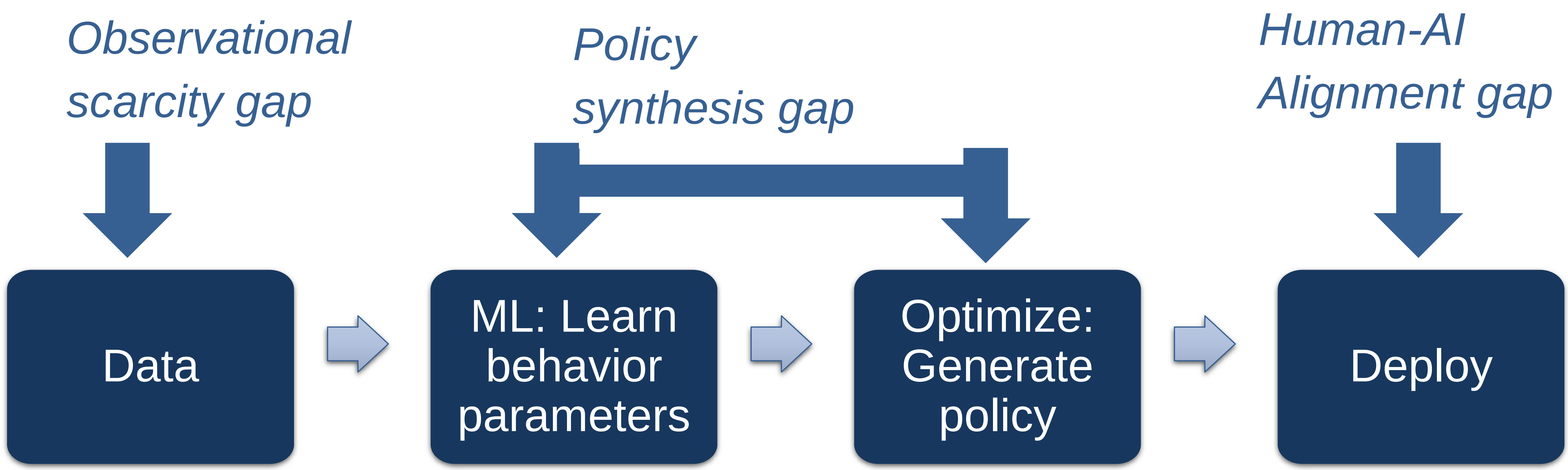
Maximize coverage across all population

Optimized allocation of 1600 health posts (AAAI'26)



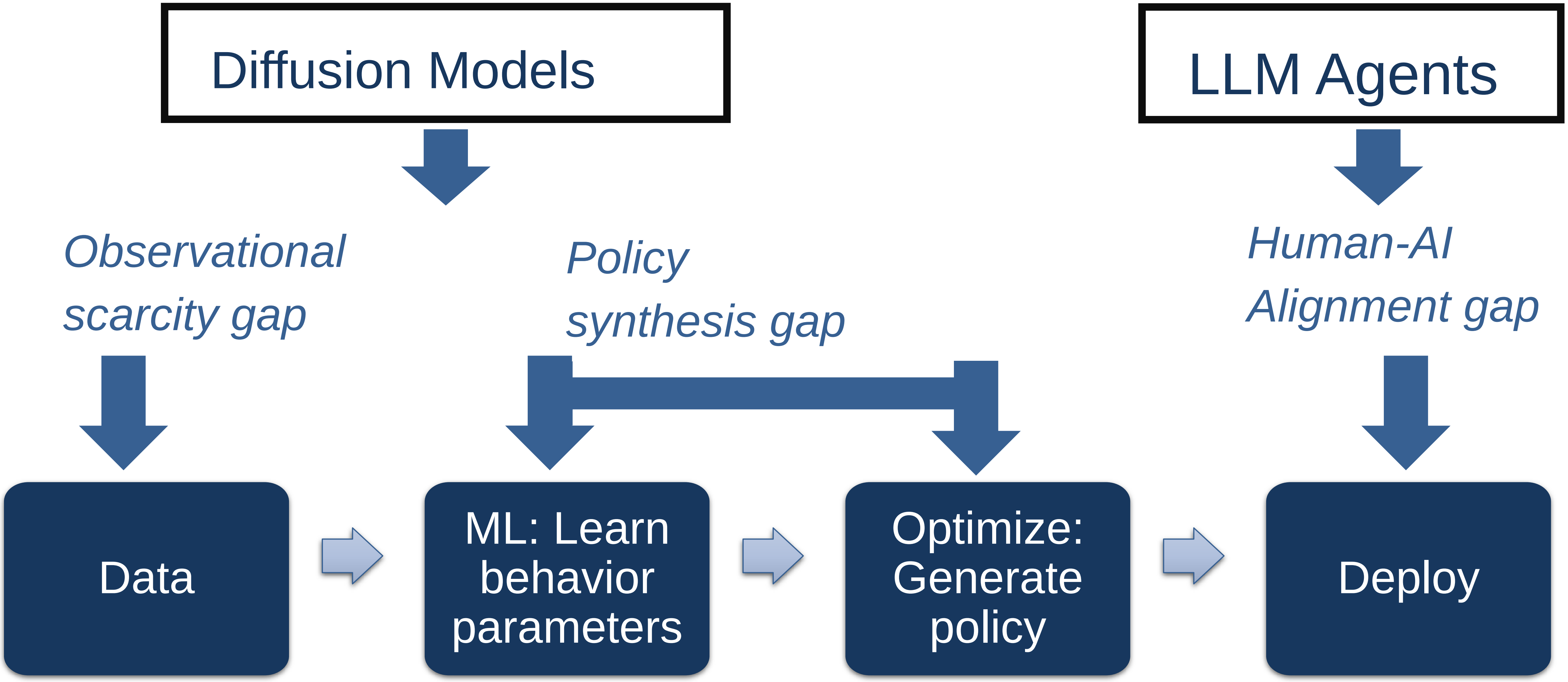
On going collaboration

AI4SI Deployment Bottleneck:
Spans the Data-to-Deployment Pipeline



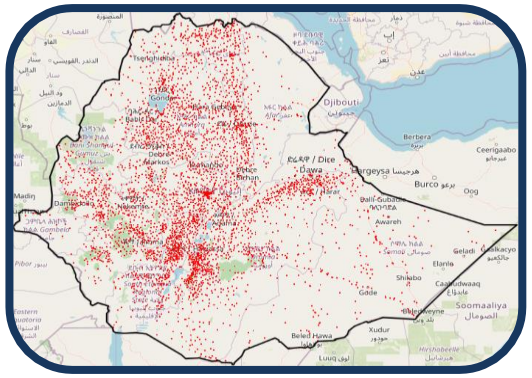
Generative AI for AI4SI Deployment Bottleneck:
LLM Agents & Diffusion Models

Generative & Agentic AI: Address deployment bottleneck



Human AI Alignment Gap

Health post allocation, Ethiopia



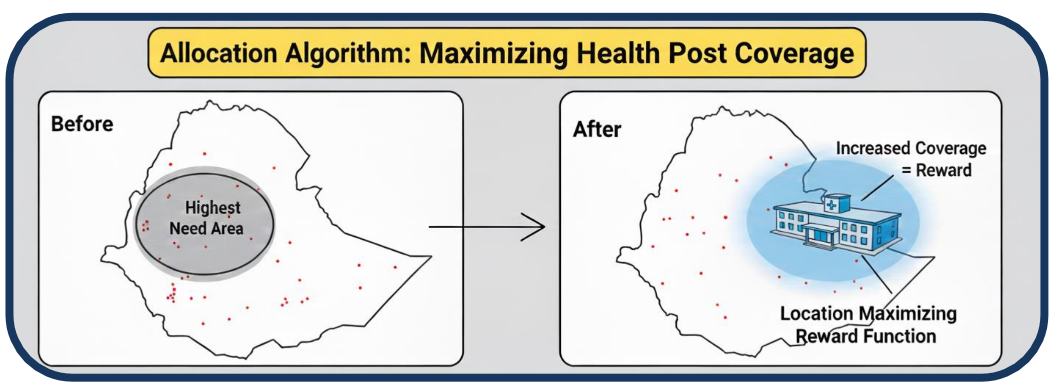
Maximize coverage across all population

+

Prioritize peripheral districts

Prioritize equity among key districts

Human AI Alignment Gap



Service call allocation, ARMMAN

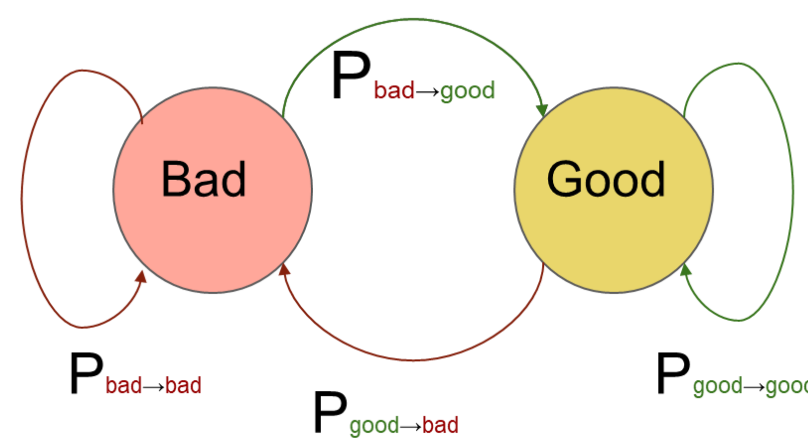
Maximize listenership across all beneficiaries

+

Slightly prioritize late shift workers

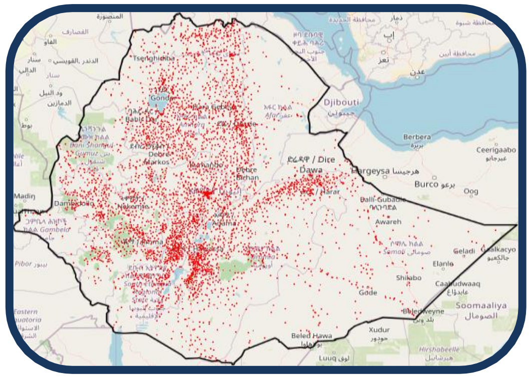
Prioritize technologically challenged

Human AI Alignment Gap



Human AI Alignment Gap

Health post allocation, Ethiopia



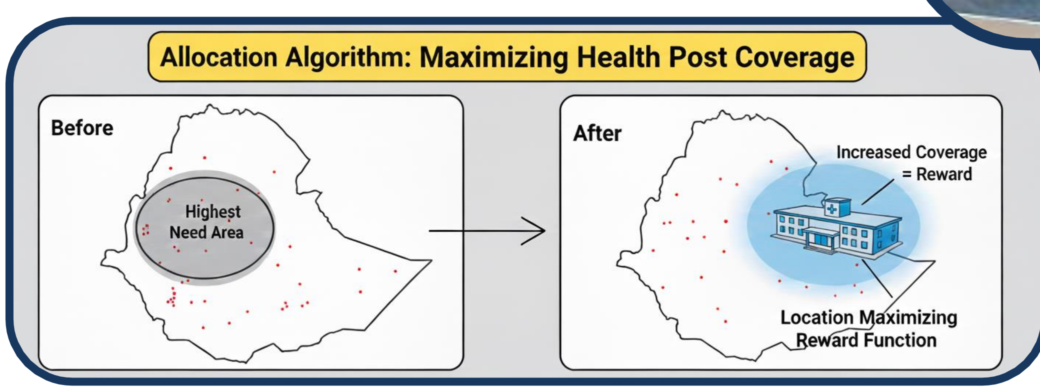
Maximize coverage across all population

+

Prioritize peripheral distric

Prioritize equity among key

Human AI Alignment G



Service call allocation, ARMMAN

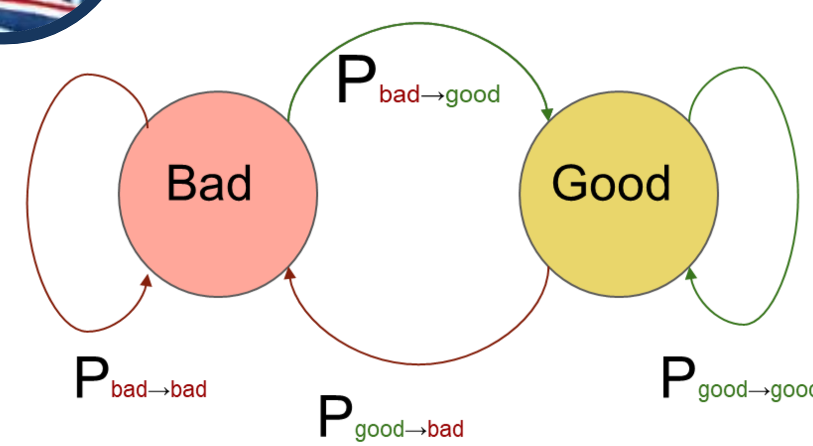
Maximize listenership across all beneficiaries

+

prioritize late shift workers

technologically challenged

Human AI Alignment Gap

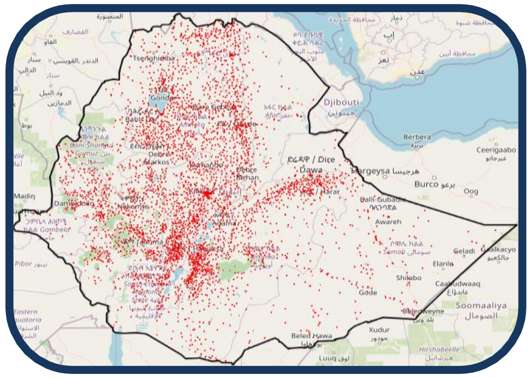


LLM Agents to Address Human AI Alignment Gap

Vibe Coding for Non-Profits

(NeurIPS 2024, ICML 2025, AAAI 2026a,b, AAMAS 2026)

Health post allocation, Ethiopia



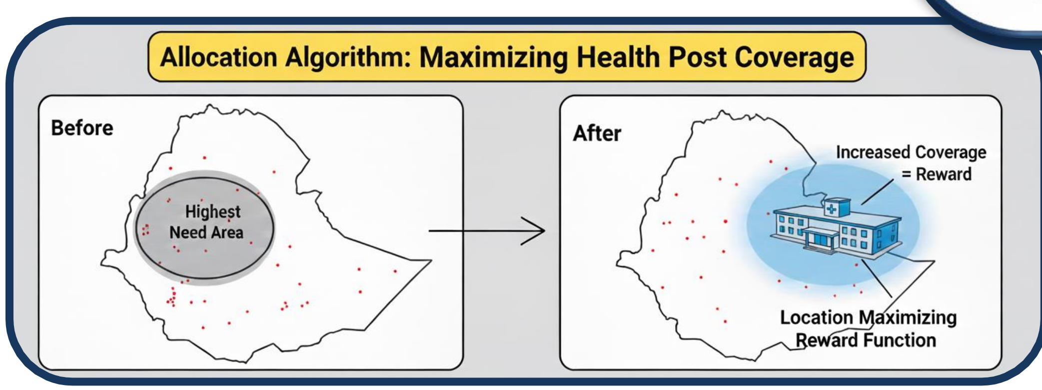
Maximize coverage across all population

\+

Prioritize peripheral distric

Prioritize equity among key

Human AI Alignment G



Service call allocation, ARMMAN

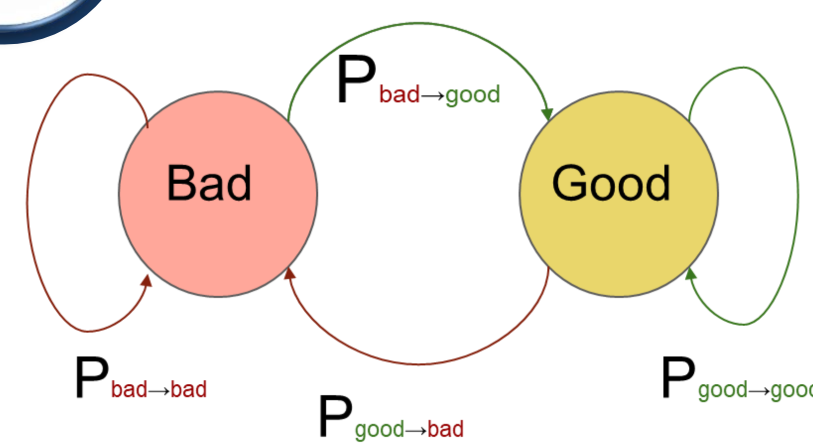
Maximize listenership across all beneficiaries

\+

prioritize late shift workers

technologically challenged

Human AI Alignment Gap



The End