Optimization and Planning of Limited Resources for Improving Maternal and Child Health

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CMU Guest Lecture

February 2023

Maternal and Child Health

- 1 woman dies every 20 min in childbirth
- 4 out of 10 children too thin/short

➔ **Most of these are preventable!**

Credit: WHO/ Blink Media - Veejay Villafranca

Credit: WHO SEARO

ARMMAN's mission

Reduce maternal, neonatal and child mortality and morbidity in underprivileged communities

" Pregnancy is not a disease. Childhood is not an ailment. Dying due to a natural life event is not acceptable. "

- Dr. Aparna Hegde, Founder of ARMMAN

Serves 26 Million women, across 19 Indian States

Image Courtesy: ARMMAN

ARMMAN mMitra program

- Automated voice messages: 2 calls/week
- 17% increase in infants with tripled birth weight at end of year
- 36% increase in women knowing importance of taking iron tablets

- ***Key Challenge:***
  Upto 50% women drop-off from mMitra
- *Limited staff for live service call intervention*

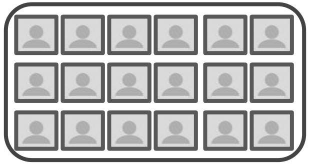
Use AI to pre-empt and prevent dropouts

Immersive Field Visits

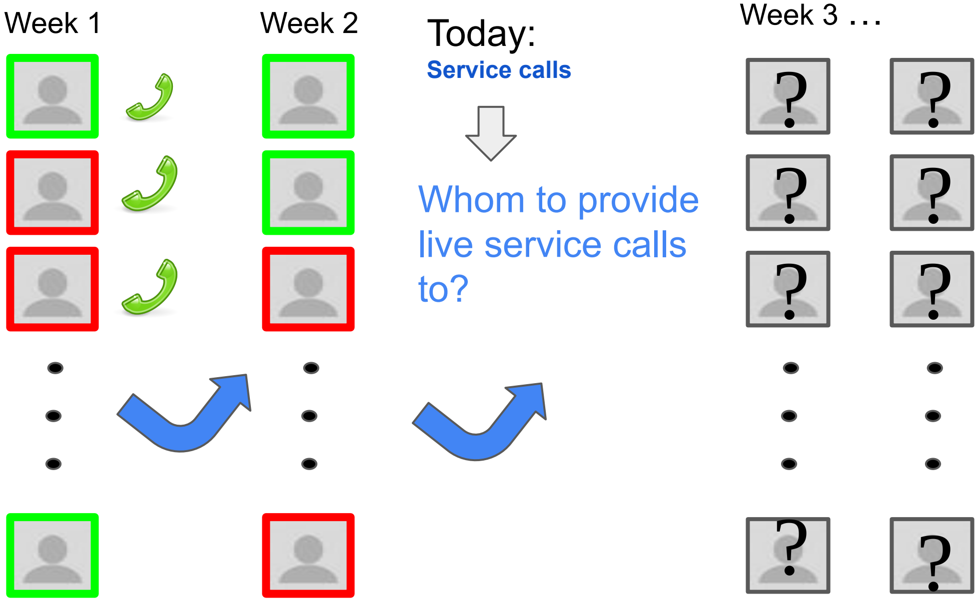
On-ground interactions with health-workers and beneficiaries

Limited Resources: Service Call Allocation Problem

- 23,000 mothers



- 450 service calls/week



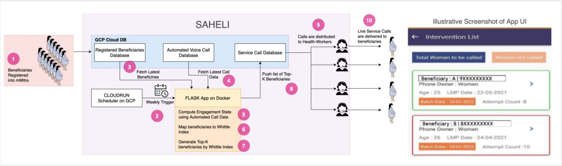
➢ **Whom to provide service call to and when?**

Deployed “SAHELI”

➢ **Whom to provide service call to and when?**

Relevant Data
All mothers
Engagement status
Demographic information

SAHELI



Which mothers to call this week

(IAAI 2023)
Innovative Application Award

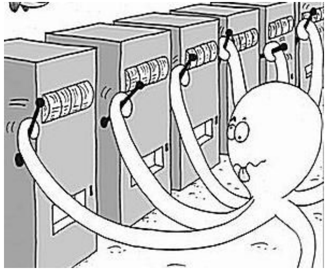
Restless Multi-Armed Bandit

Similar to Stochastic Multi-Armed Bandits

Cast this as an RMAB problem

- **N** arms
- Choose *m* per round to maximize benefit
- E.g.: 23,000 beneficiaries, 450 arms

More complicated than regular Multi-Armed Bandits …

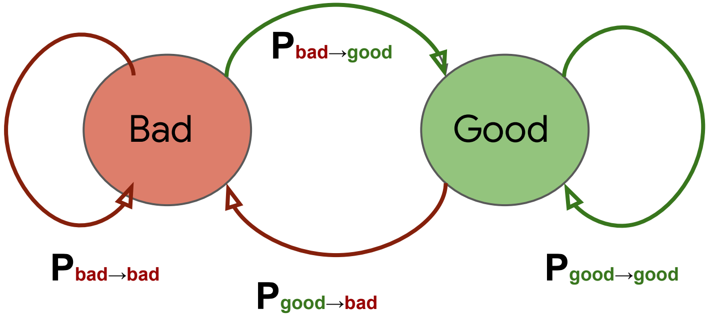


- Each arm has “state”
- Spontaneous state change (even when arm not pulled)
- Reward obtained from all arms (even arms that are not pulled)

Restless Multi-Armed Bandit

Each beneficiary (arm) is a Markov Decision Process (MDP)

States - Binary Valued



A "bad" state and a "good" state
s = 0 s = 1

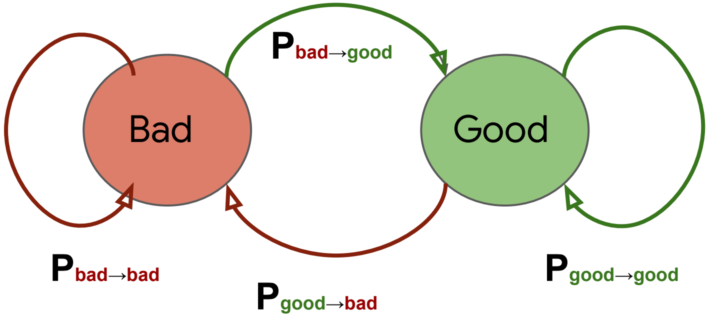
Good/Bad State:
Engaged/ Not Engaged
(with an automated voice call)

Call Engagement:
Beneficiary listens to > 30sec

Restless Multi-Armed Bandit

Each beneficiary (arm) is a Markov Decision Process (MDP)

States - Binary Valued



A “bad” state and a “good” state
s = 0 s = 1

Actions


passive


active

Place Service Call or Not Place Service Call

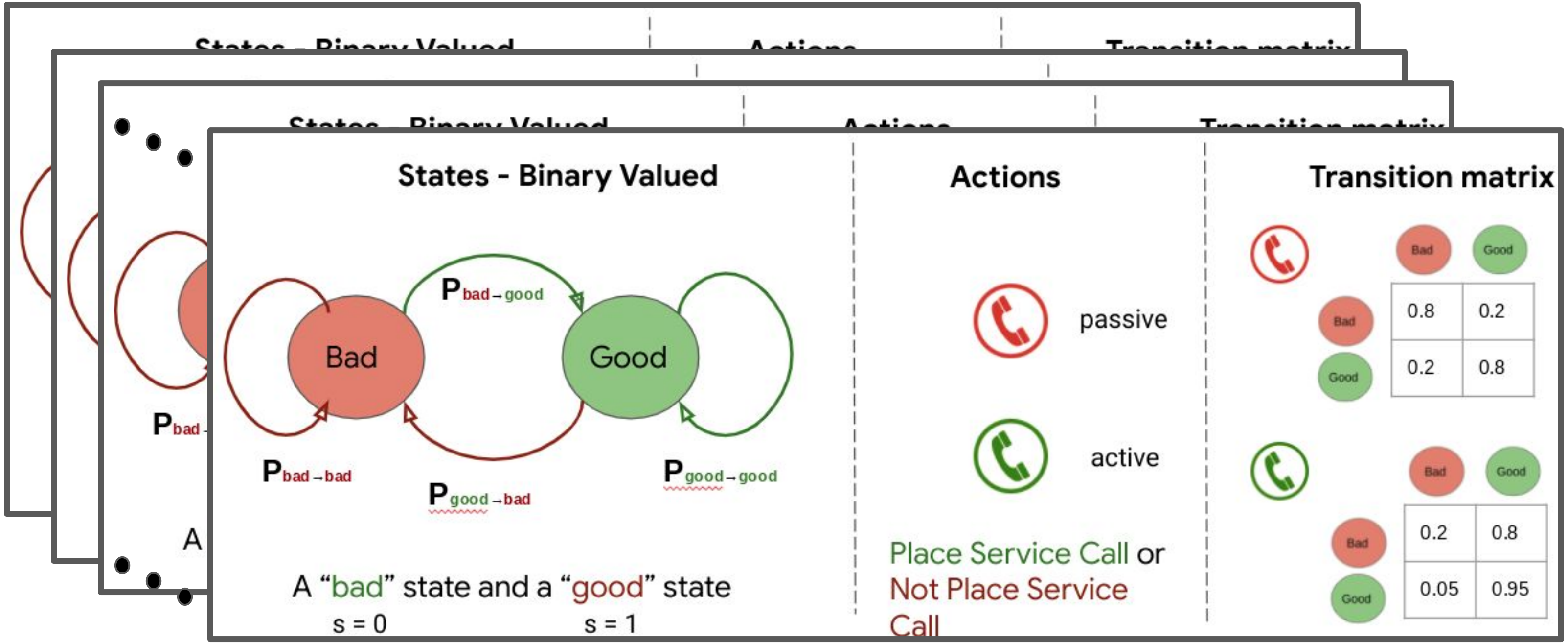
Transition matrix

	Bad	Good
Bad	0.8	0.2
Good	0.2	0.8

	Bad	Good
Bad	0.2	0.8
Good	0.05	0.95

Restless Multi-Armed Bandit

N arms. Pick k arms for service call delivery



RMAB Solution: Whittle Index [P. Whittle 1988]

- Intuitively, Whittle Index = “value for acting” on each arm.

- Improvement in (future) engagement as a result of intervention

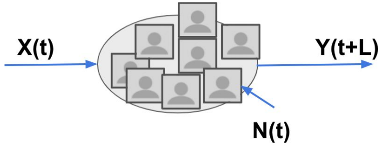
Index:	0.1	0.7	0.2
Mother:			

Fundamental Issues with existing work...

Existing RMAB techniques don't work out-of-the-box

Combinatorial action space: **~100s of mothers; takes ~hours** to compute
*Need to scale to **millions of mothers**, no computing cluster with NGO*

Dynamically Changing Population
New beneficiaries enroll and existing beneficiaries leave



Infer Unknown parameters
Never seen real-world deployment because input parameters are unknown

Contributions

Roadmap for this talk...

Scale to millions of mothers ***Fast algorithms, 1000x speed-up***	*Collapsing Bandits* ***(NeurIPS'2020)***
Dynamically Changing Population ***Adaptive interpolation algorithms***	*Streaming Bandits* ***(AAMAS'2022)***
Whiteboard → Real-world results ***Novel Clustering techniques; Field trial with 23,000 mothers***	*Real-world RMAB evaluation* ***(AAAI'2022)***

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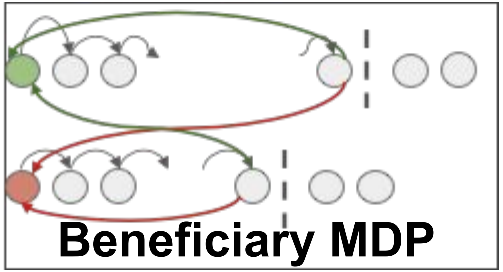
Optimality of Threshold Policies

> ***Theorem: Threshold policies are optimal if effect of service calls on "non-engaging" mothers is large***

- What are threshold policies?

Service Call → **Wait until threshold condition met** → **Service call again** → **Repeat**

Threshold Whittle: Fast Index Algorithm



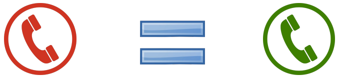
Compute Stationary distribution for thresholds {X1, X2}:

$\pi\ (X1, X2)$

Average reward under policy π

$R_{avg}\ (X1, X2)$

Construct *indifference equations* whose solution yields “index” (non-trivial step)



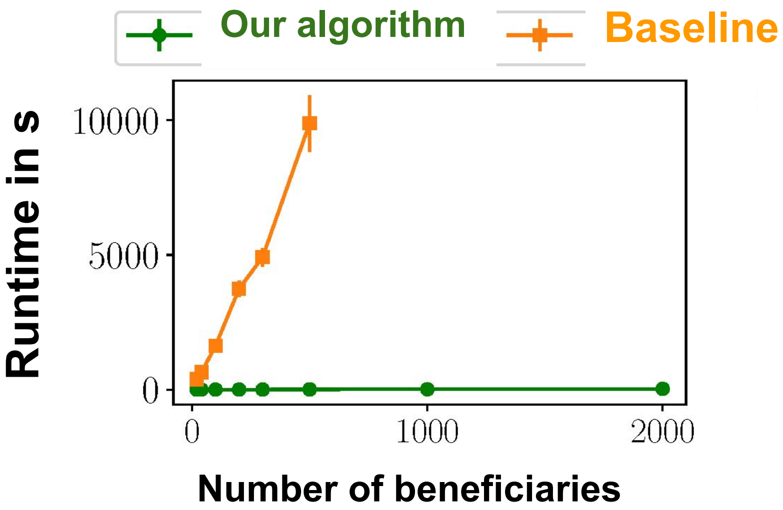
Solve for index

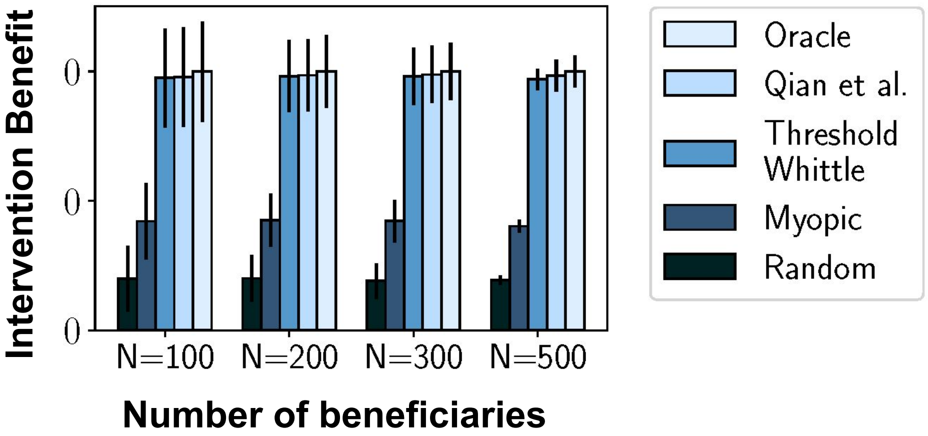
$

*Index = “How much do I have to pay you **not** to place service call”*

Empirical Results

- Runs 1000x faster
- No sacrifice on performance





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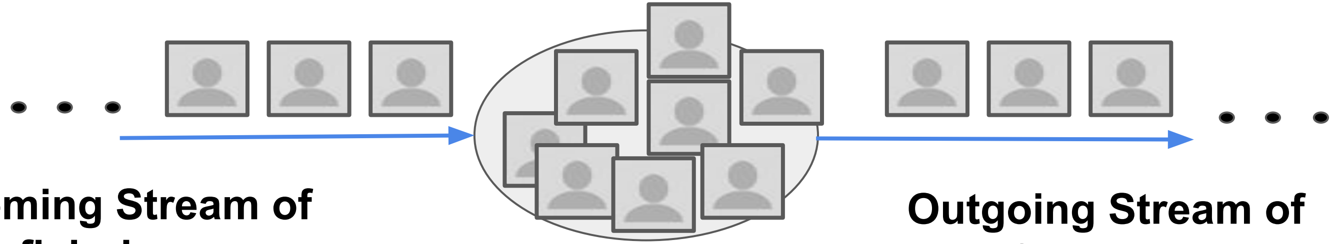
Two Additional Challenges

1. Finite horizon:
   Length of health programs usually finite and can be rather small

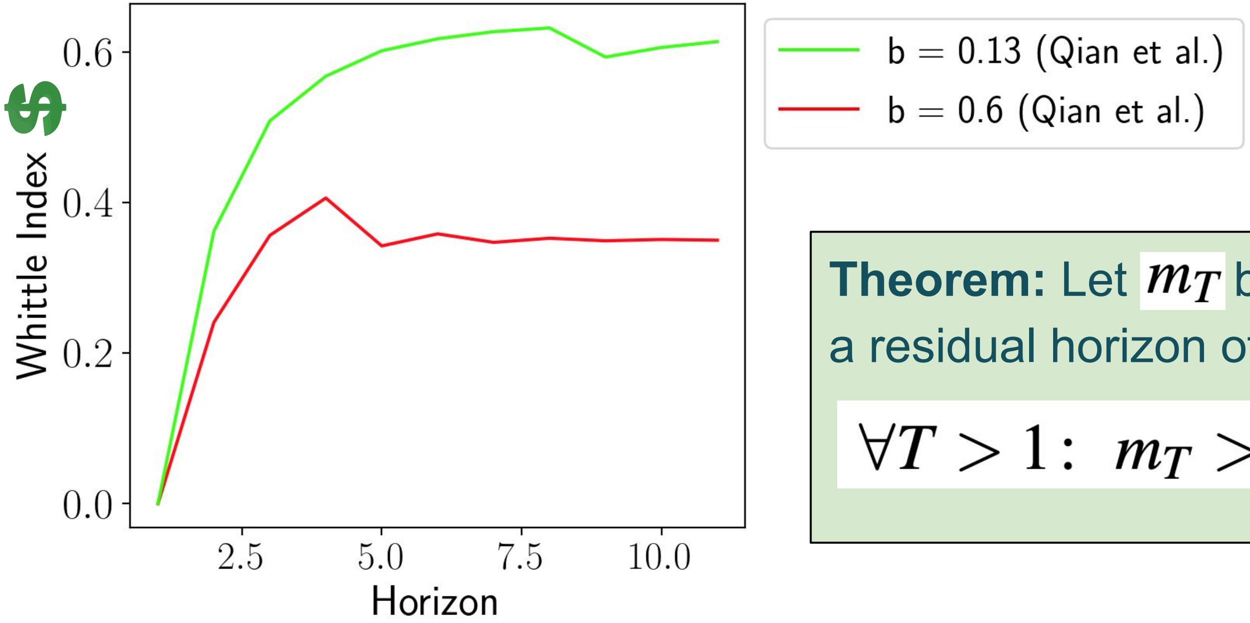
2. Streaming Arms:
   New mothers arrive each day. Existing enrolled mothers leave each day.



Incoming Stream of Beneficiaries

Outgoing Stream of Beneficiaries

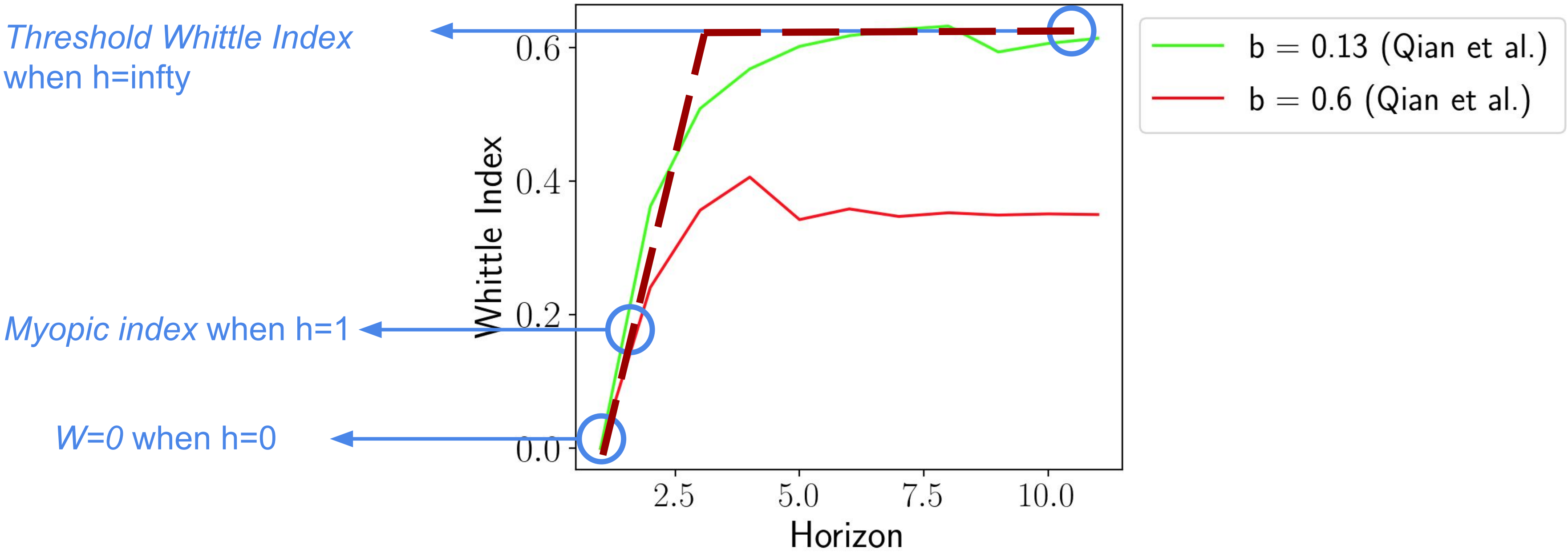
Key Issue: Index Decay



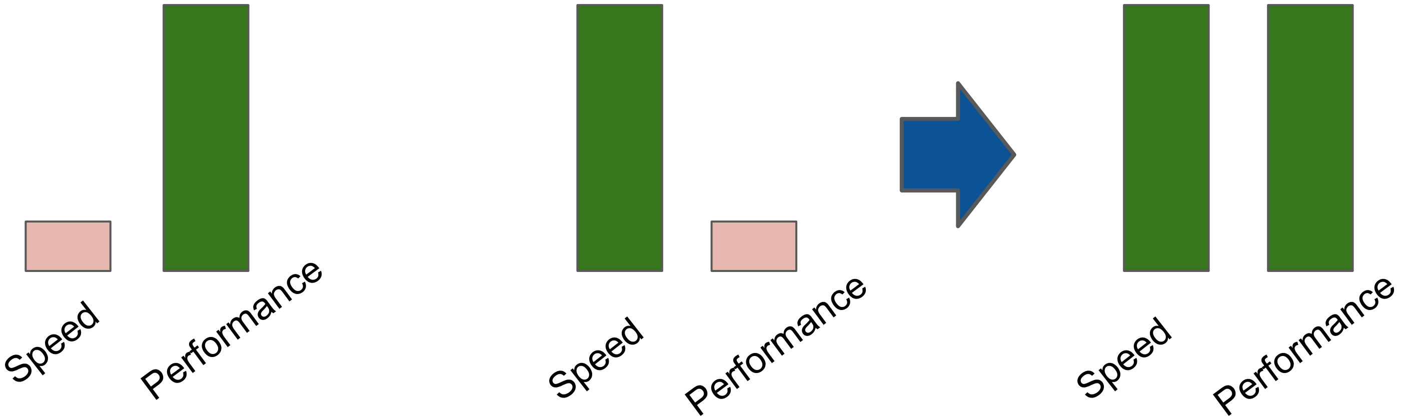
Theorem: Let m_T be the Whittle Index for a residual horizon of T. Then:

$$\forall T > 1: \;\; m_T > m_1 > m_0 = 0$$

Solution: Index Interpolation



Result: Great Runtime, without performance sacrifice



Baseline 1 **Baseline 2** **Interpolation Algorithm**

Contributions

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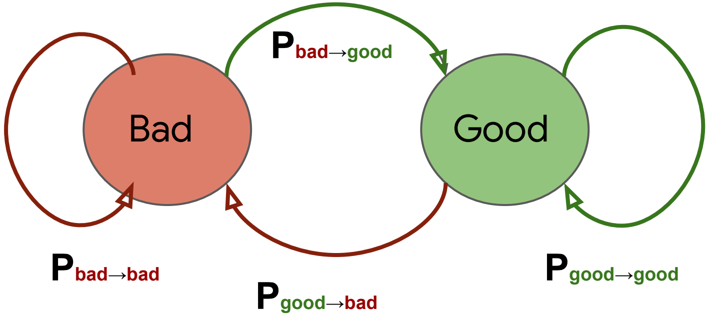
Key Challenge: Unknown RMAB Parameters

Unknown for real-world mothers

States - Binary Valued



Actions

passive

active

Transition matrix

Passive:

	Bad	Good
Bad	0.8	0.2
Good	0.2	0.8

Active:

	Bad	Good
Bad	0.2	0.8
Good	0.05	0.95

Available Data

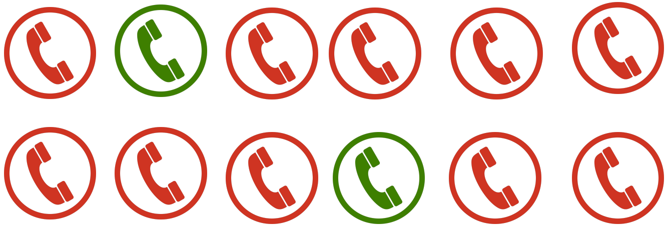
Unknown for real-world mothers

Transition matrix

	Bad	Good
Bad	0.8	0.2
Good	0.2	0.8

	Bad	Good
Bad	0.2	0.8
Good	0.05	0.95

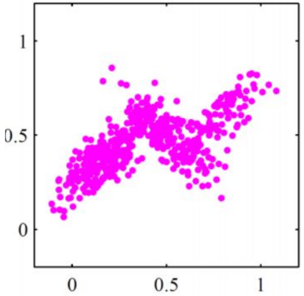
Actions received:



- ➢ Passive samples are abundant but Interventions are rare
- ➢ Some may *never* see interventions

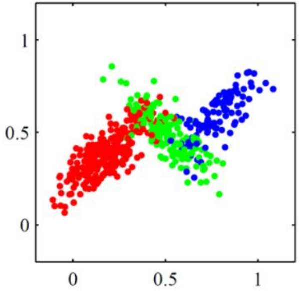
Infer from Historical Data

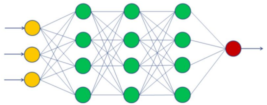
Training Step:
With historical batch data:



Passive transition probability data:
Gives a coarse prior f(.)

Clustering

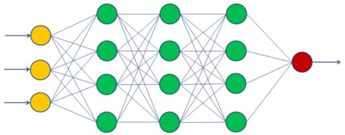




Learn a map from features ⟶ cluster

Testing Step:
New, unseen beneficiaries:

features



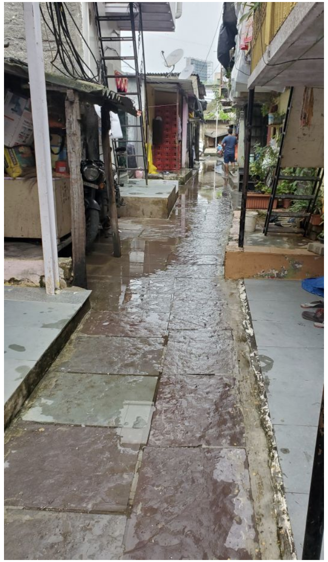
Predict clusters
[0.3, 0.1, **0.6**]

Optimize RMAB Service Call Allocation

Real-world Field Study

★ *First large-scale deployment of restless bandits for public health*

Study with 23000 beneficiaries



Setup: Service Quality Improvement Study

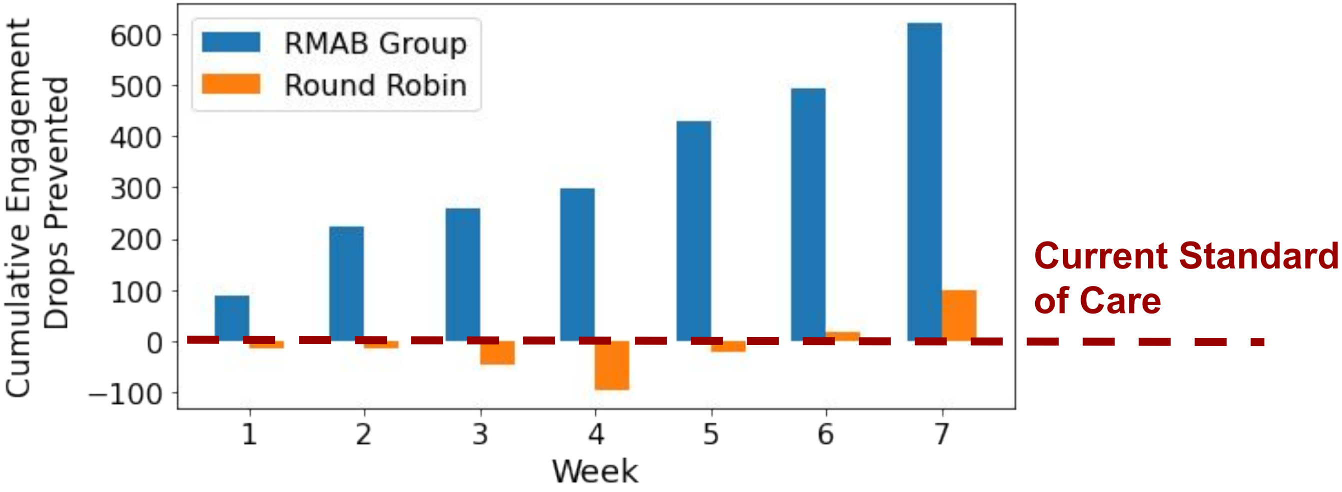
- ➔ 23,000 beneficiaries ⟶ randomly divide 3 groups:

Current Standard of Care (CSOC) Benchmark Listenership.	**Round Robin**: Call beneficiaries in a set order.	**RMAB** Our Algorithm

- ➔ 7667 beneficiaries per group
- ➔ Service call to 225 mothers per week
- ➔ **Objective**: Measure engagement (drop)

  – How much engagement drop was prevented

Results: Real-world Study with 23000 beneficiaries



Conclusion:

RMAB cuts beneficiary engagement drop by ~ 30% compared to CSOC

Results: Statistical significance

RMAB *statistically significantly reduces engagement drops*

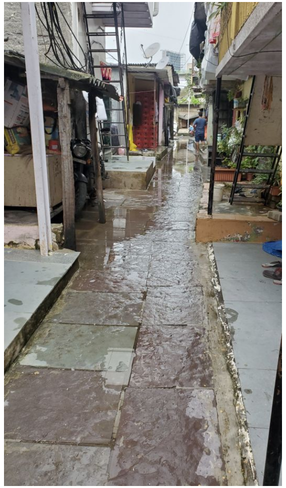
	RMAB vs CSOC	RR vs CSOC	RMAB vs RR
% reduction in cumulative engagement drops	32.0%	5.2%	28.3%
p-value	0.044*	0.740	0.098†

Lessons Learned

- **Domain partnerships with NGOs**
  Field-visits and on-the-ground discussions crucial

- **Data and compute limitations**
  Genuine research challenges

- **Deploying AI systems for social impact**
  Critical technical challenges to deploying at scale



Testimonials and Goals

*“We have seen that when women listen to the information, the health outcomes are phenomenal. **We are able to reach out to more and more women each week, bring them back into the fold and save lives because of AI.**”*

- ***Dr. Aparna Hegde,** Founder of ARMMAN*

*“I was unable to listen to the calls earlier. Then didi (staff) called and even came over, they explained the benefits of listening to the messages. Now I listen to the calls regularly, it feels like someone from your own family is looking after you. **I follow all the advice and take good care of my baby.**”*

- ***Pooja,** Mother of a 5 months old*

Next Goal: Scale up AI-enabled service to 1 million women

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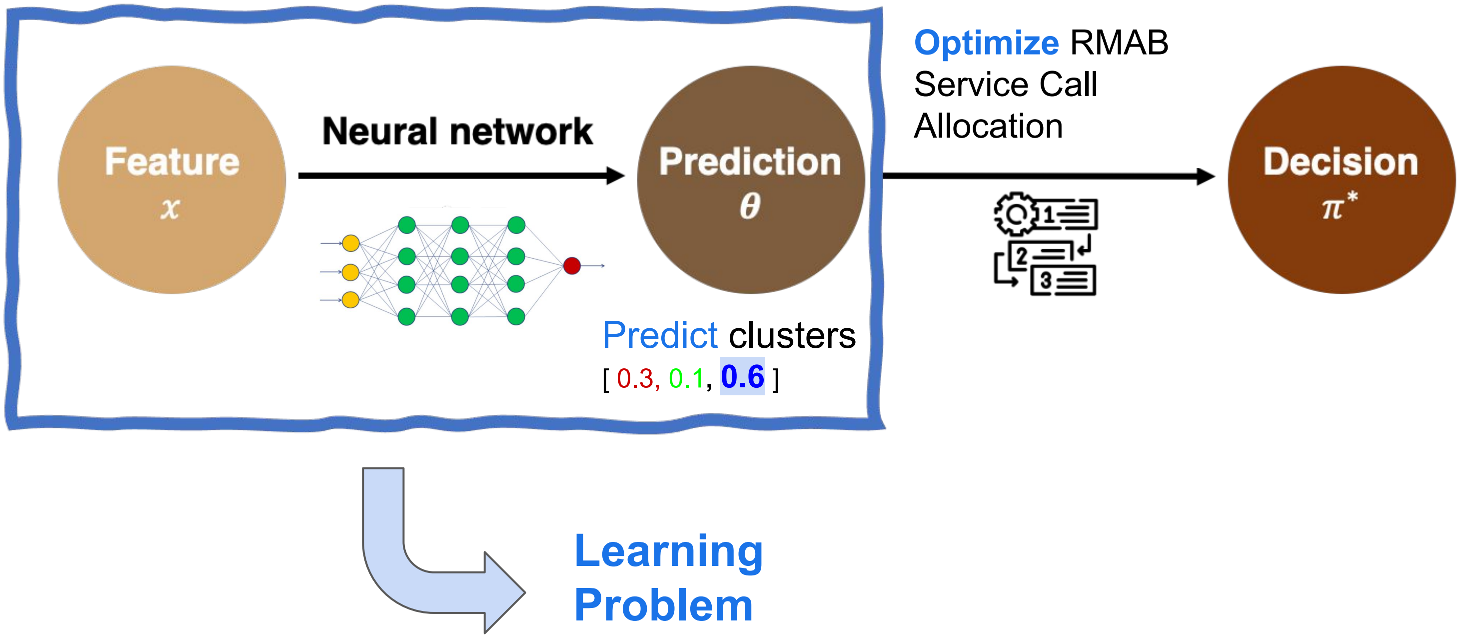
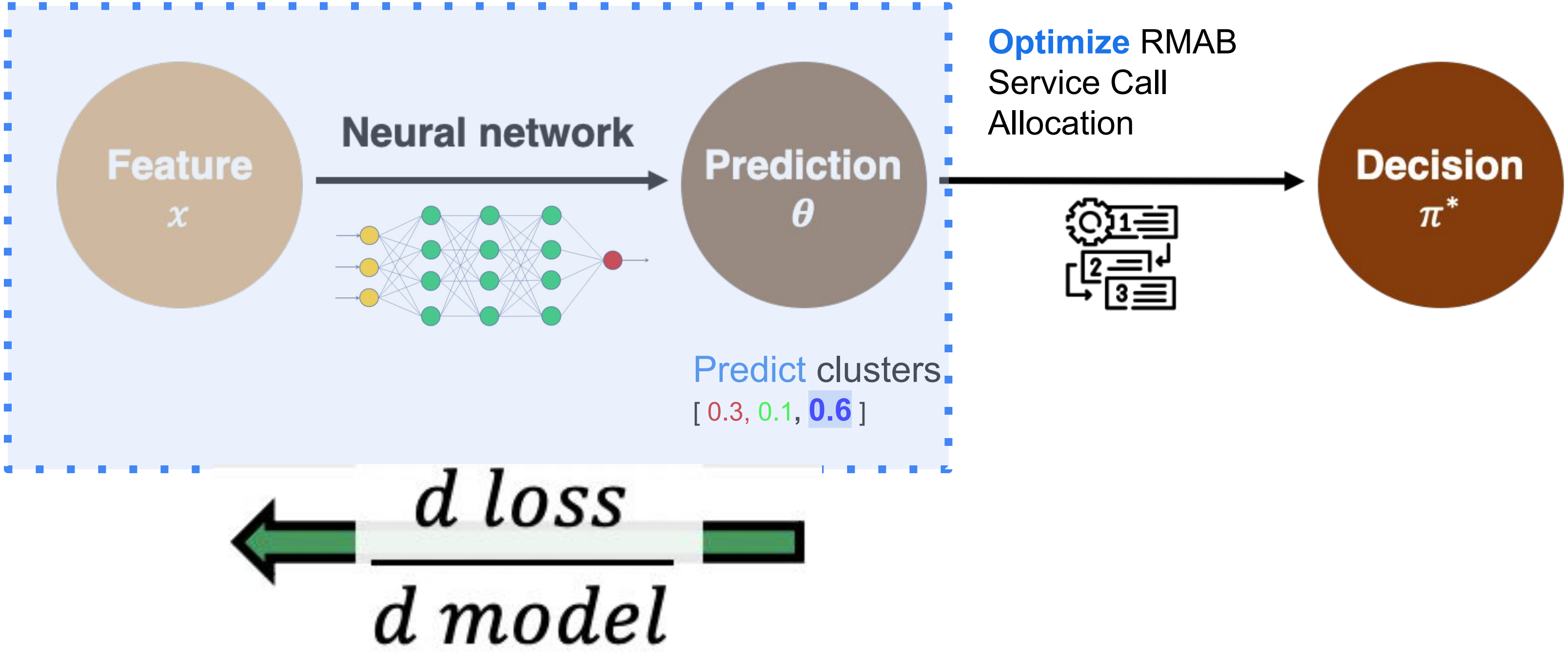
1. Decision-Focused Learning *(AAAI 2023)*

Testing Step:

New, unseen beneficiaries:



Current Approach: Predict-then-Optimize



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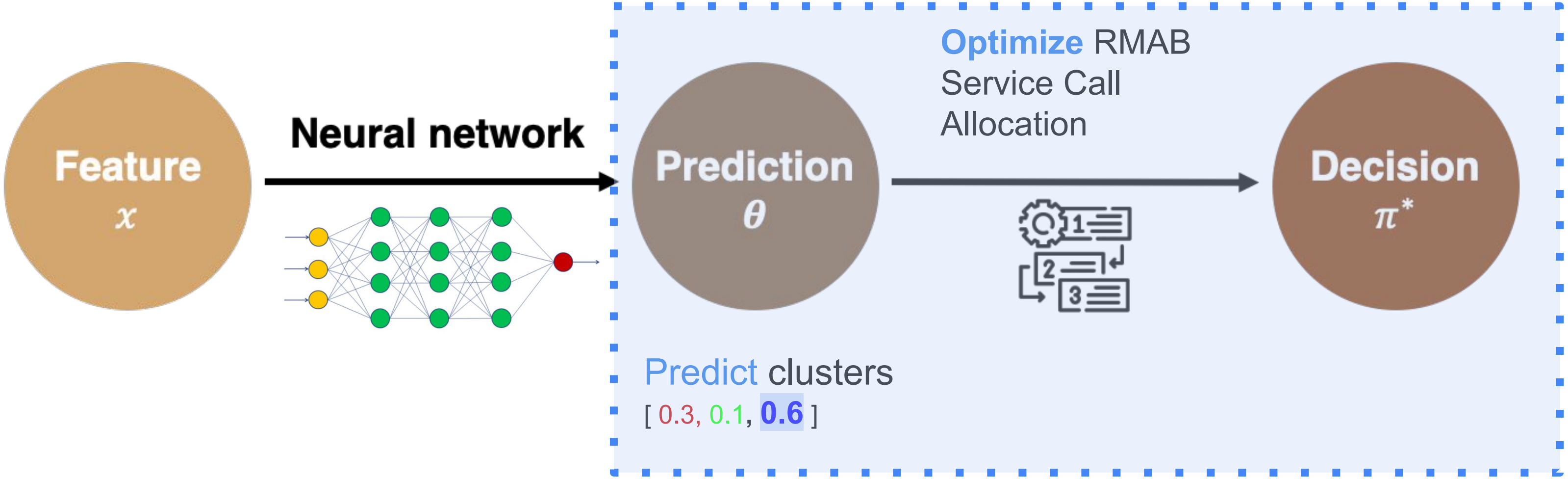
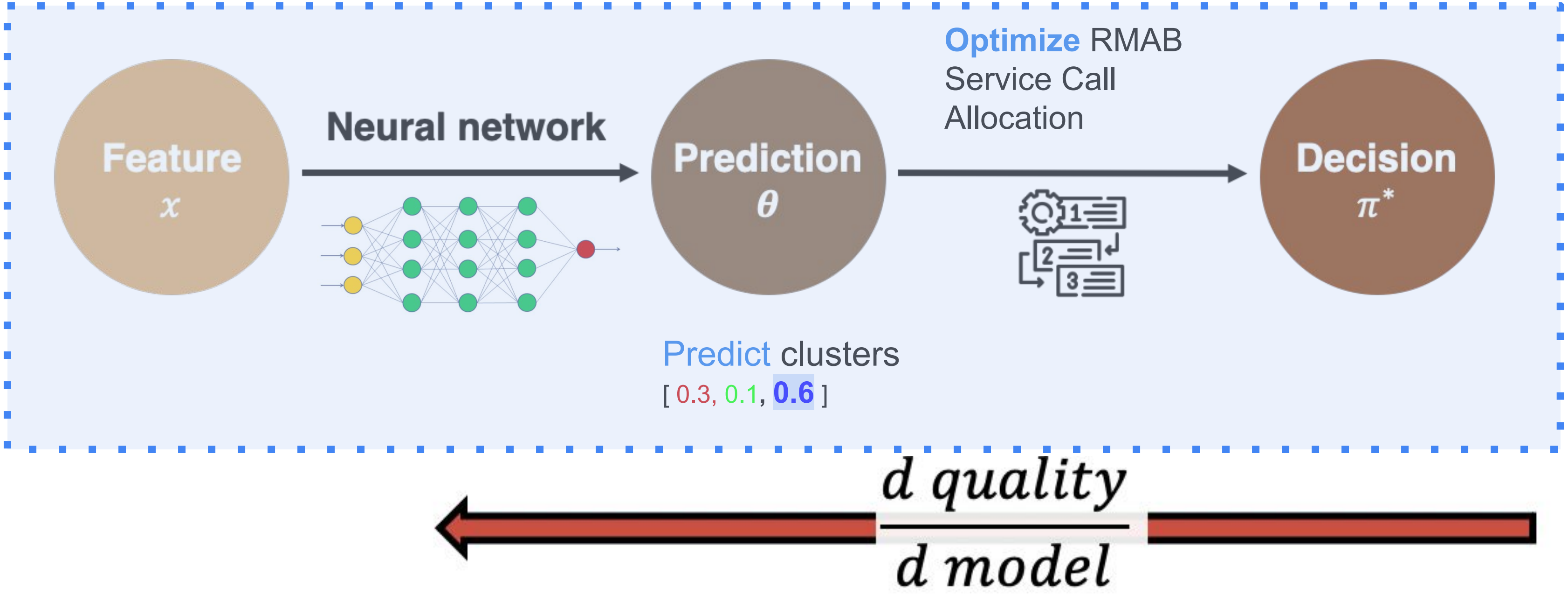


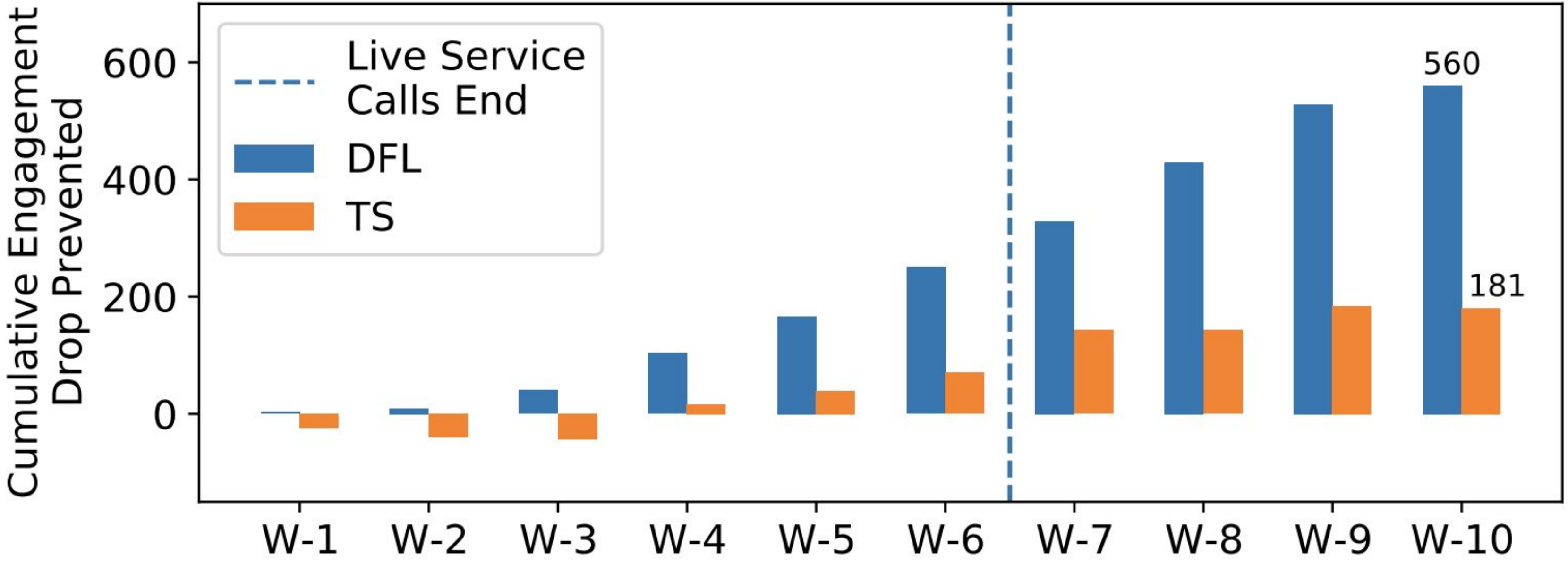
Improved Approach: Decision-Focused Learning



(AAAI 2023)

2. Field Trial: Decision-Focused Learning vs Two-Stage

(AAMAS 2023)

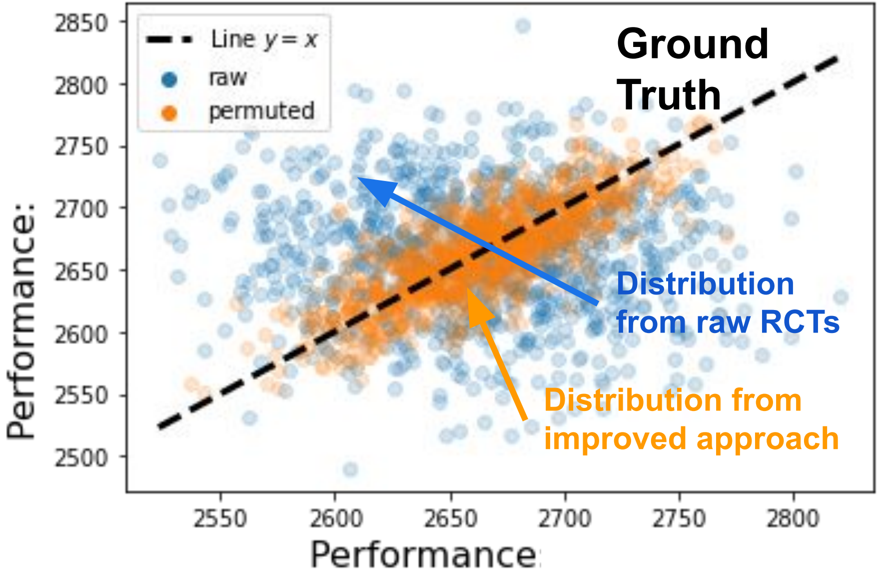


3. Improved Policy Evaluation through RCTs

(joint work with Prof. Bryan Wilder, under submission to ICML 2023)

❑ **Unique Challenges in Resource Allocation RCTs:**

- **Each RCT is 1 sample**
- **(in contrast, standard RCTs yield N samples)**



THANK YOU!

Presented by: **Aditya Mate**

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