Improving Human Sequential Decision-Making with Reinforcement Learning

Park Sinchaisri

UC Berkeley Haas

Stanford GSB OIT Seminar

March 6, 2024

Research Overview

1. Behavioral Operations
for the Future of Work

Research Overview

1 Behavioral Operations for the Future of Work

Gig Workers' Decision-Making / Pricing

- Behavioral & economic drivers on workers' labor decisions/scheduling
  (with Gad Allon, Maxime Cohen, M&SOM 2023)
- Multihoming, incentive schemes
  (with Gad Allon, Maxime Cohen, Ken Moon, under review at Management Science)
- Pricing with quality perception
  (with Rim Hariss, Georgia Perakis, Karen Zheng, Major Revision at M&SOM)

Gig Workers' Learning

- Optimizing task selection/assignment to improve learning
  (with Shunan Jiang, work in progress)

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2 Human-AI Interfaces in Operations

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Tips for Sequential Decision-Making

- Learning best practices from data and mining simple advice
  (with Hamsa Bastani, Osbert Bastani, Minor Revision at Management Science)
- Precision of advice in uncertain environment
  (with Philippe Blaettchen, preparing for submission)
- Characterizing non-adoption
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- Generative AI and productivity
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- Pricing competing products
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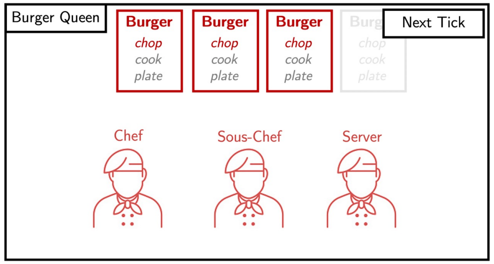

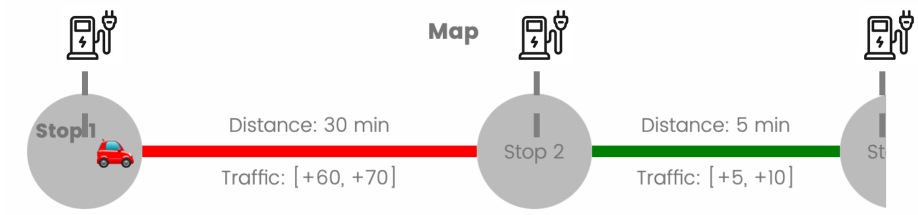

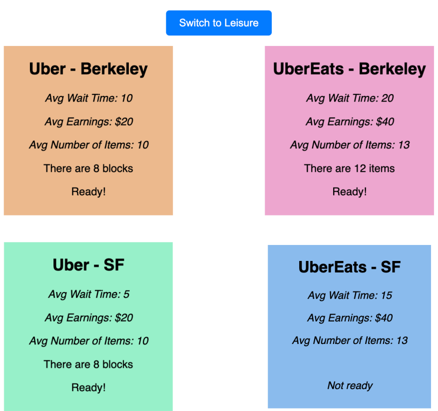

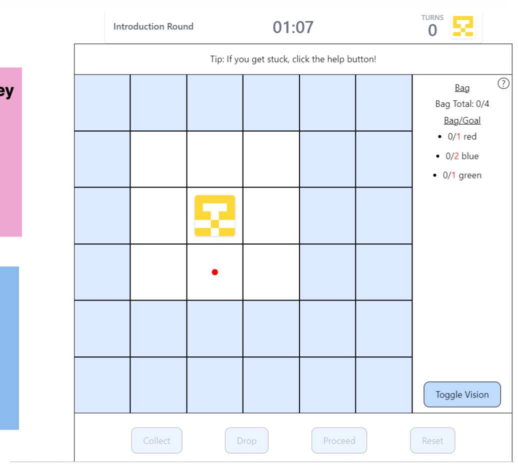

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Park Sinchaisri (UC Berkeley Haas) / parksinchaisri@berkeley.edu / parksinchaisri.github.io

Learning is Costly

2+ years

to be fully productive

$1,286/worker

training expenses

- Training Magazine 2019

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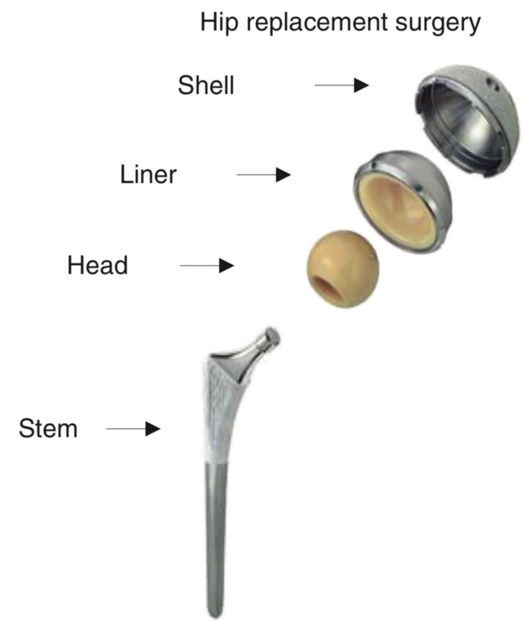


New device = **+32.4%**

surgery duration

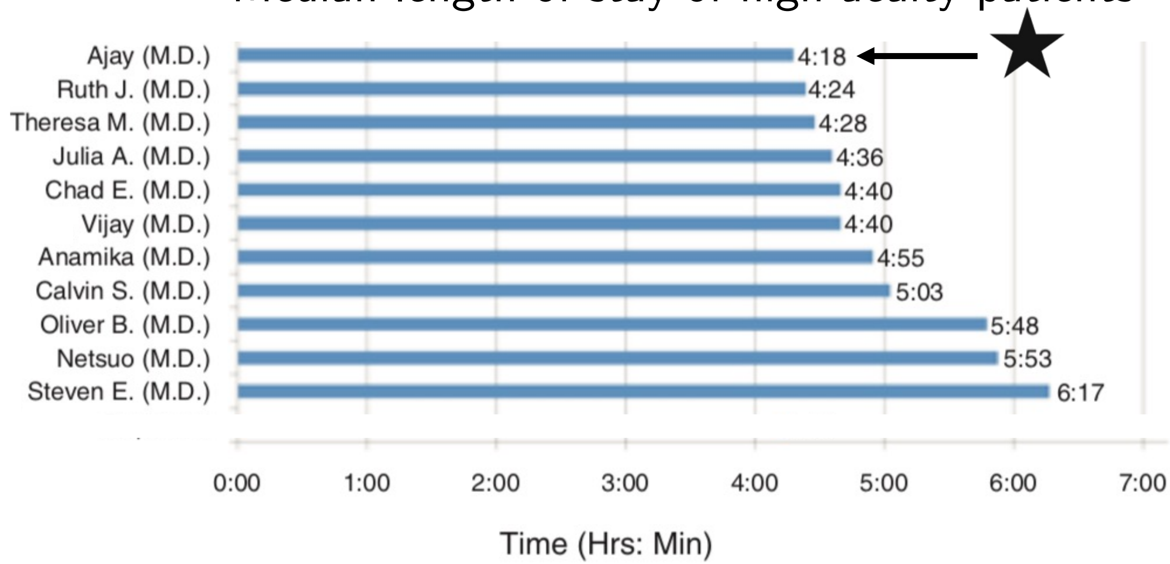
- Ramdas et al. 2018

Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019, Bavafa & Jonasson 2020, Bloom et al 2020, ...

Learning from Experts

Learning from Experts

Median length of stay of high acuity patients



- Song et al. 2018

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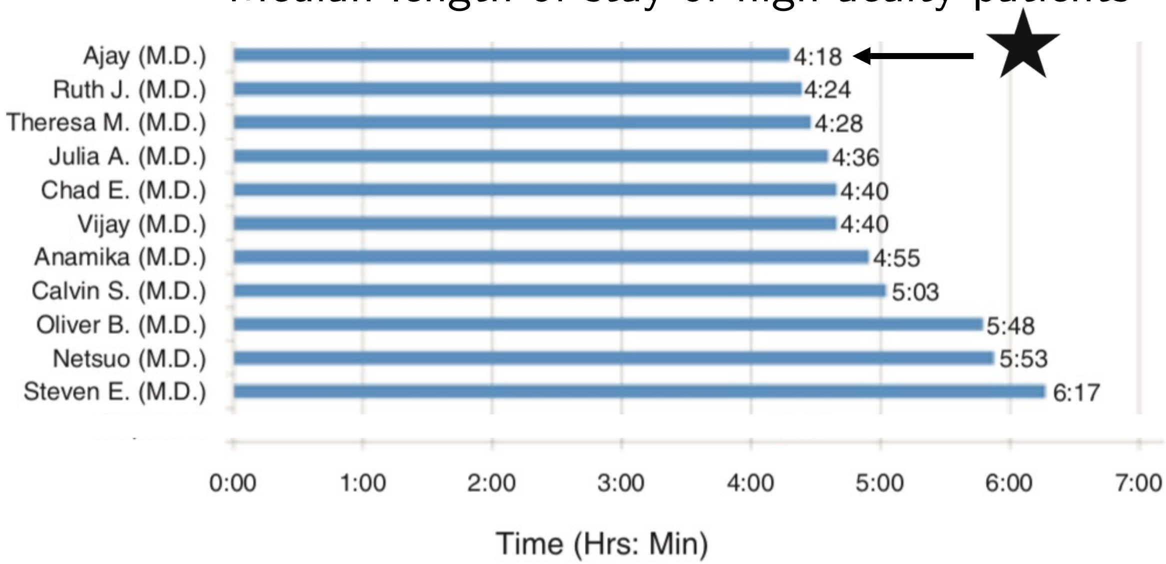

+10.9%

productivity

- Song et al. 2018

Also – Chan et al 2014, Herkenhoff et al 2018, Tan & Netessine 2019, Jarosch et al 2019, ...

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Trace Data is Everywhere

Physicians

ROACH,TRISTIN	Fibrinogen, INR, PT, PTT AMD_996304_76	MILLER,ALEX,MD *status: Unreviewed*	05•19•17
ROACH,TRISTIN	Lipitor 80 mg	MILLER,ALEX,MD *status: Unreviewed*	05•18•17
LEON,ERIN	Geriatric Wellness Visit	JONES,CAMERON,MD *status: Unreviewed*	05•16•17
BECK,ALIVIA	Zocor 20 mg	JACK,JACK,MD *status: Unreviewed, held*	05•18•17
NORTON,BETHANY	Norvasc 10 mg	MILLER,ALEX,MD *status: Unreviewed*	05•18•17
MONTGOMERY,BLAINE	Glucophage 850 mg	OSHEA,JAMIE,MD *reviewed by: PPMD_AKN...* *status: Reviewed*	05•18•17
KLECK,MICHAEL	Office Visit - Abbreviated	JONES,CAMERON,MD *reviewed by: SUSAN* *status: Reviewed*	05•12•17
MCARDLE,HELEN	Office Visit - Mobile	JONES,CAMERON,MD *status: Unreviewed*	05•12•17

Uber Drivers

Trace Data is Everywhere

Physicians

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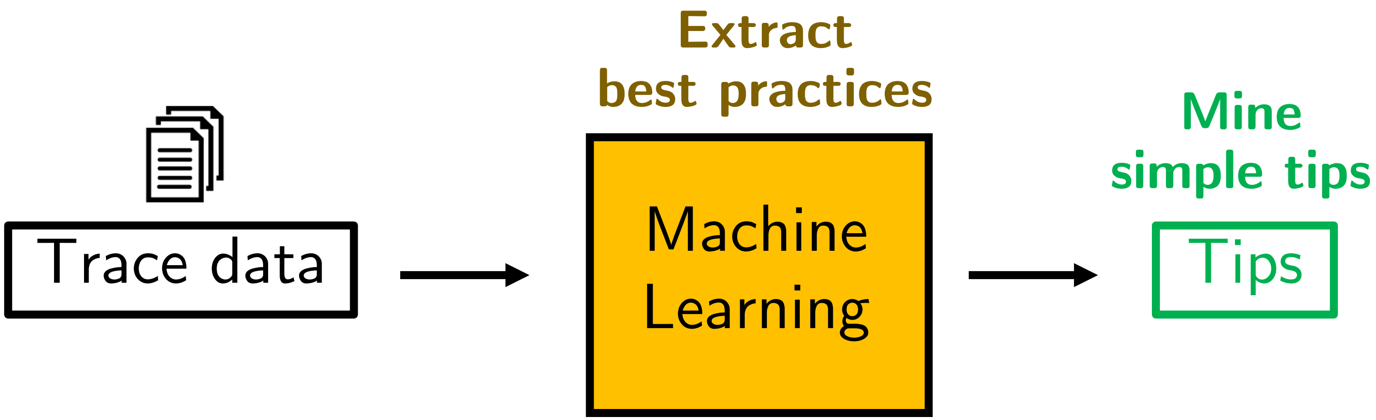
Trace data

Tips

How to Help Humans
Improve Their Decision-Making?



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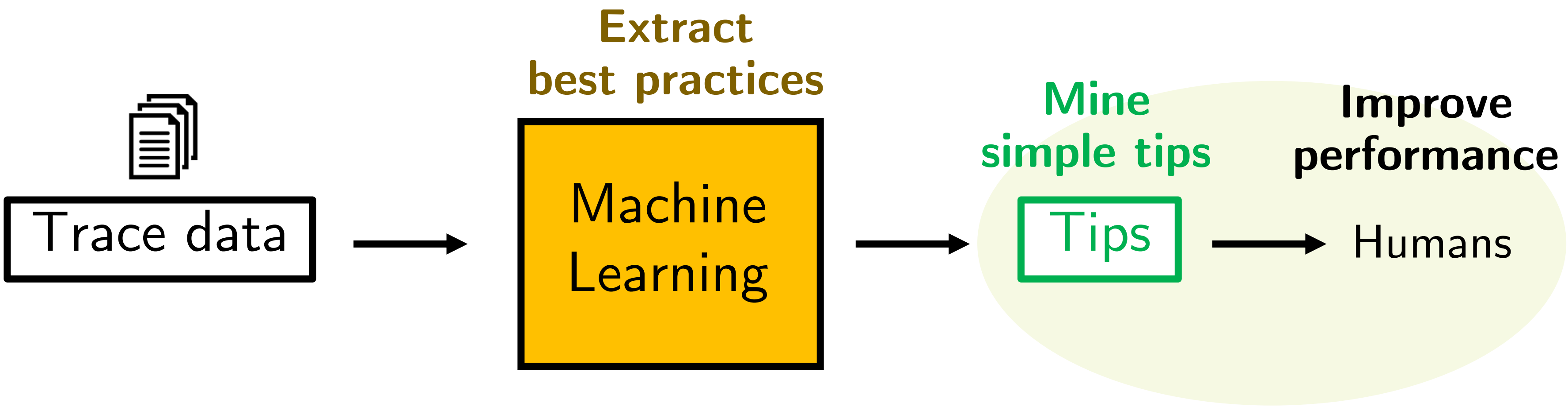

How to Help Humans
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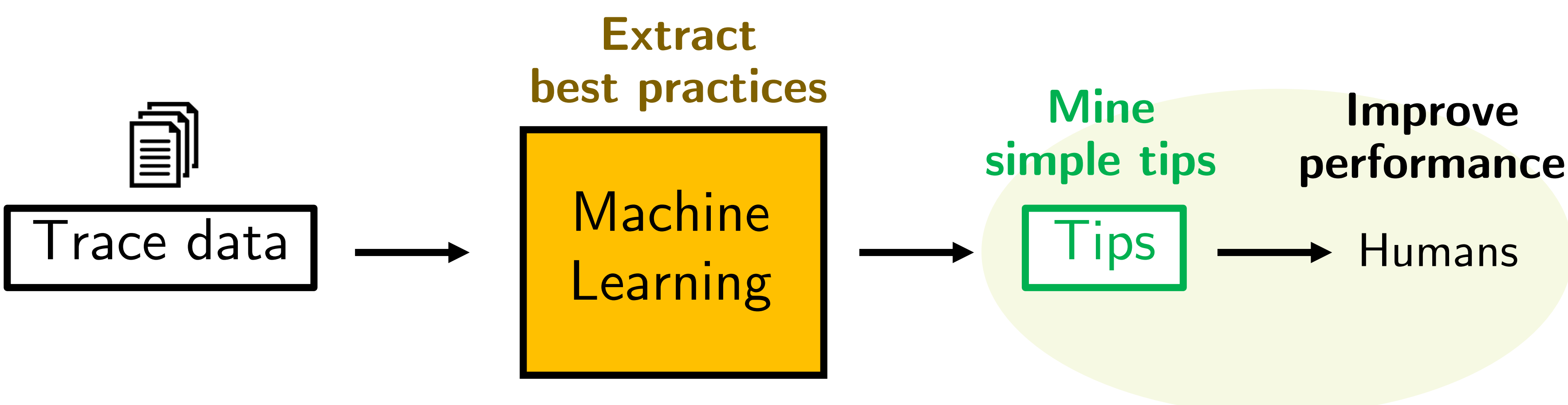
Outline:

Experimental Design
Tip Inference
Results: Performance/Compliance
Improving Compliance


with Hamsa Bastani & Osbert Bastani
Minor Revision @ Management Science



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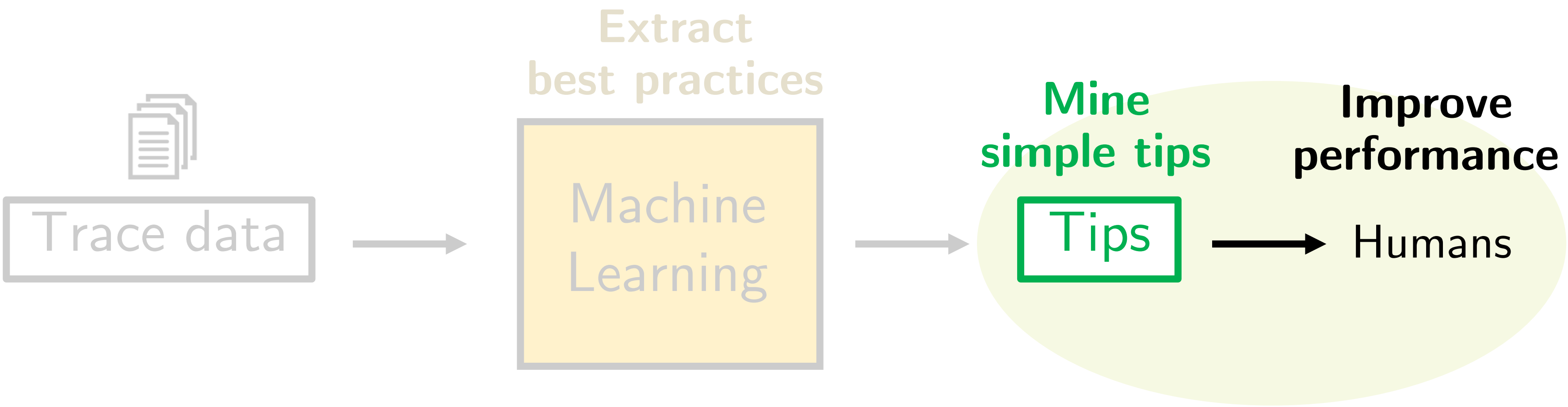
Experimental Design
+ Precision of Tips
+ Learning Post-Tip

with Philippe Blaettchen
Preparation for submission

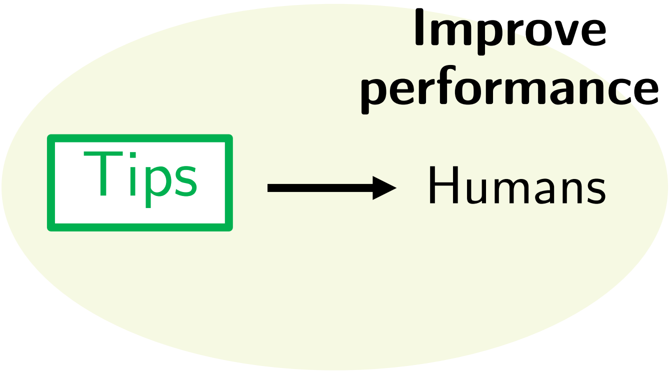
Trace data → **Extract best practices** Machine Learning → **Mine simple tips** Tips ? **Improve performance** Humans

Potential Issues



Potential Issues

- Compliance to tips, "algorithm aversion" (e.g., Dietvorst et al 2015)



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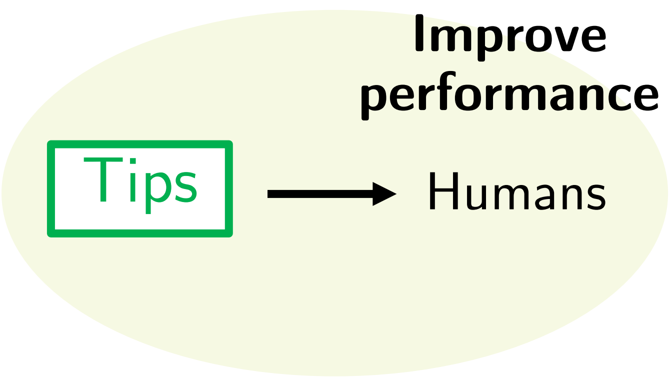

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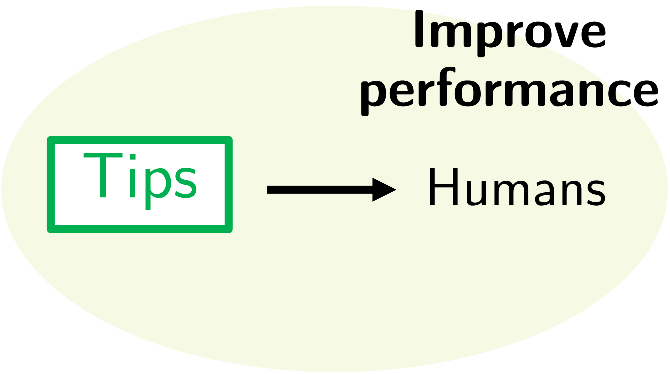

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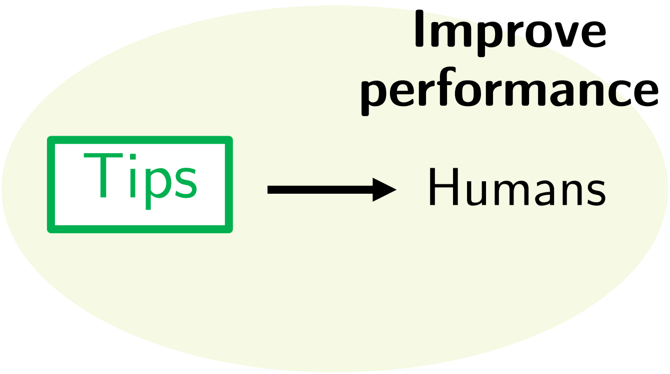
- Learning curve, spillovers



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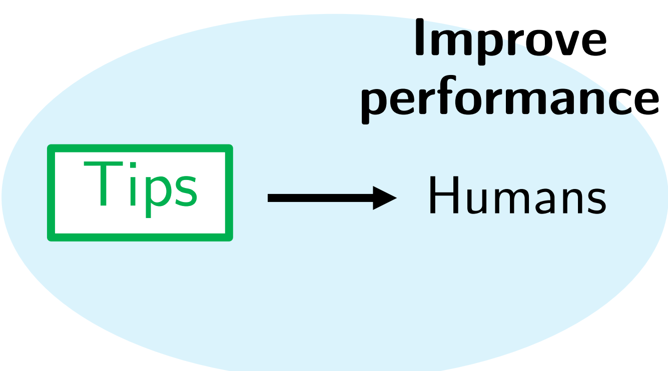
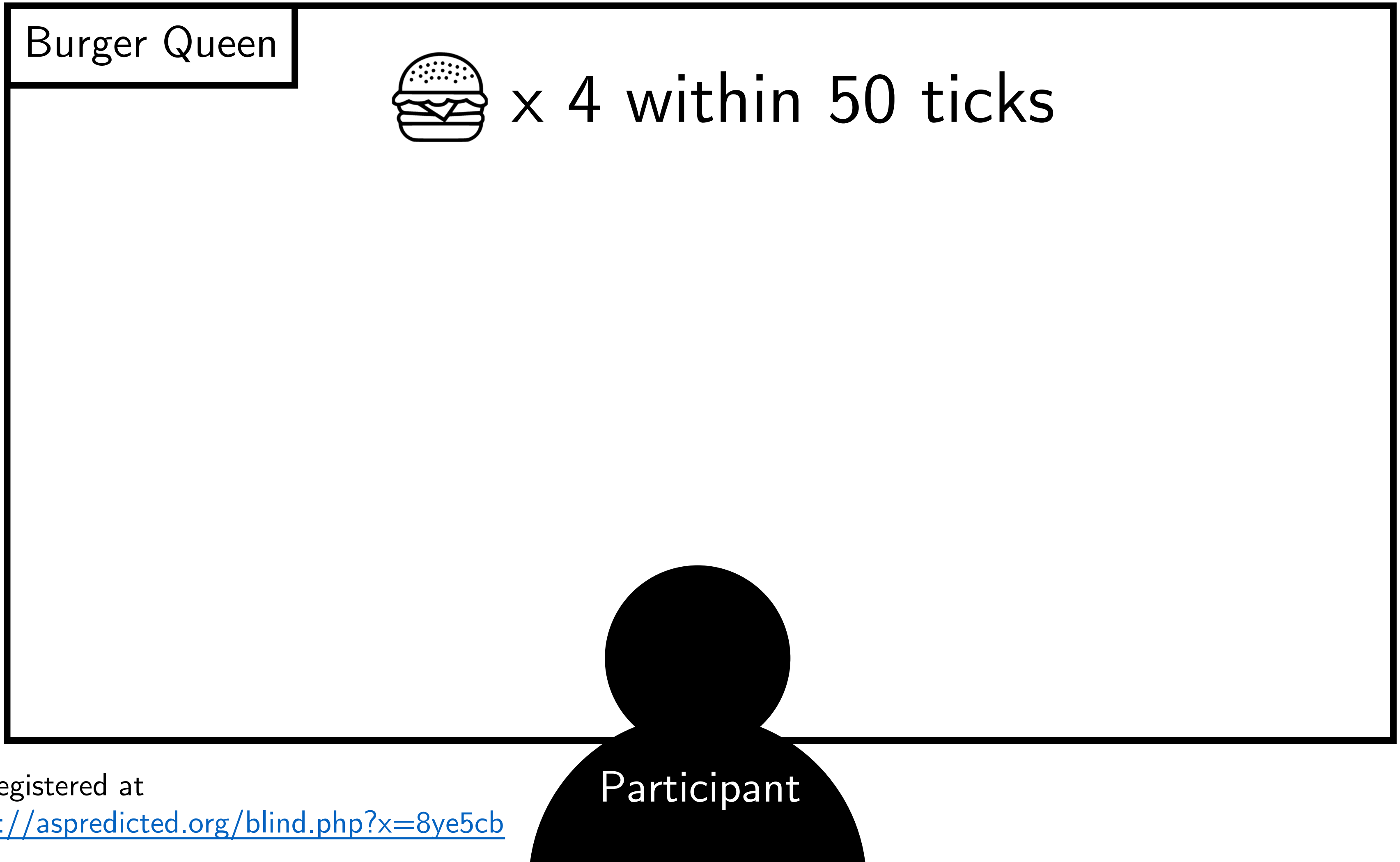
What We Did:

Controlled environment
to observe human learning
& decision-making



Study 1:

Cooking Game



Pre-registered at
https://aspredicted.org/blind.php?x=8ye5cb

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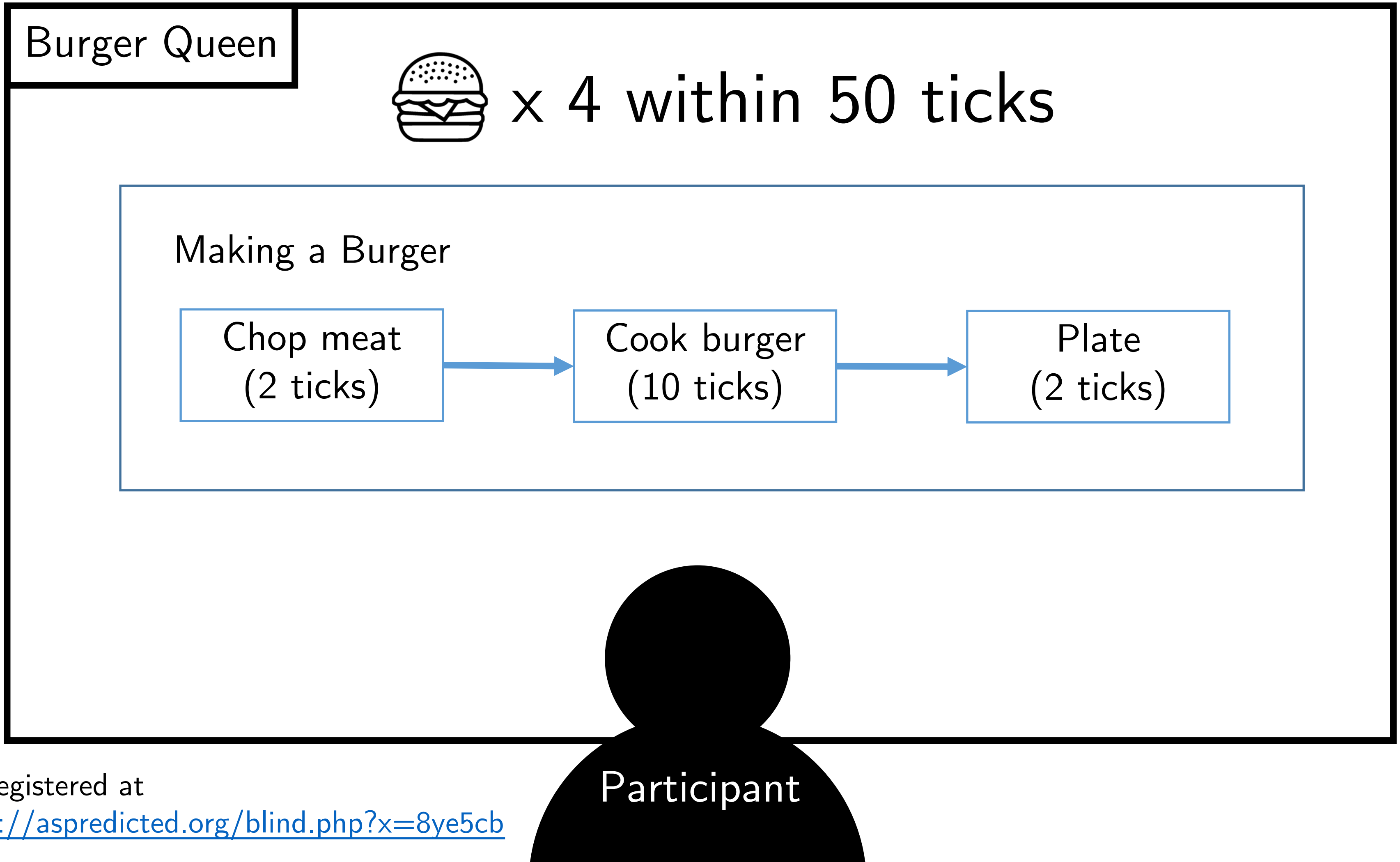

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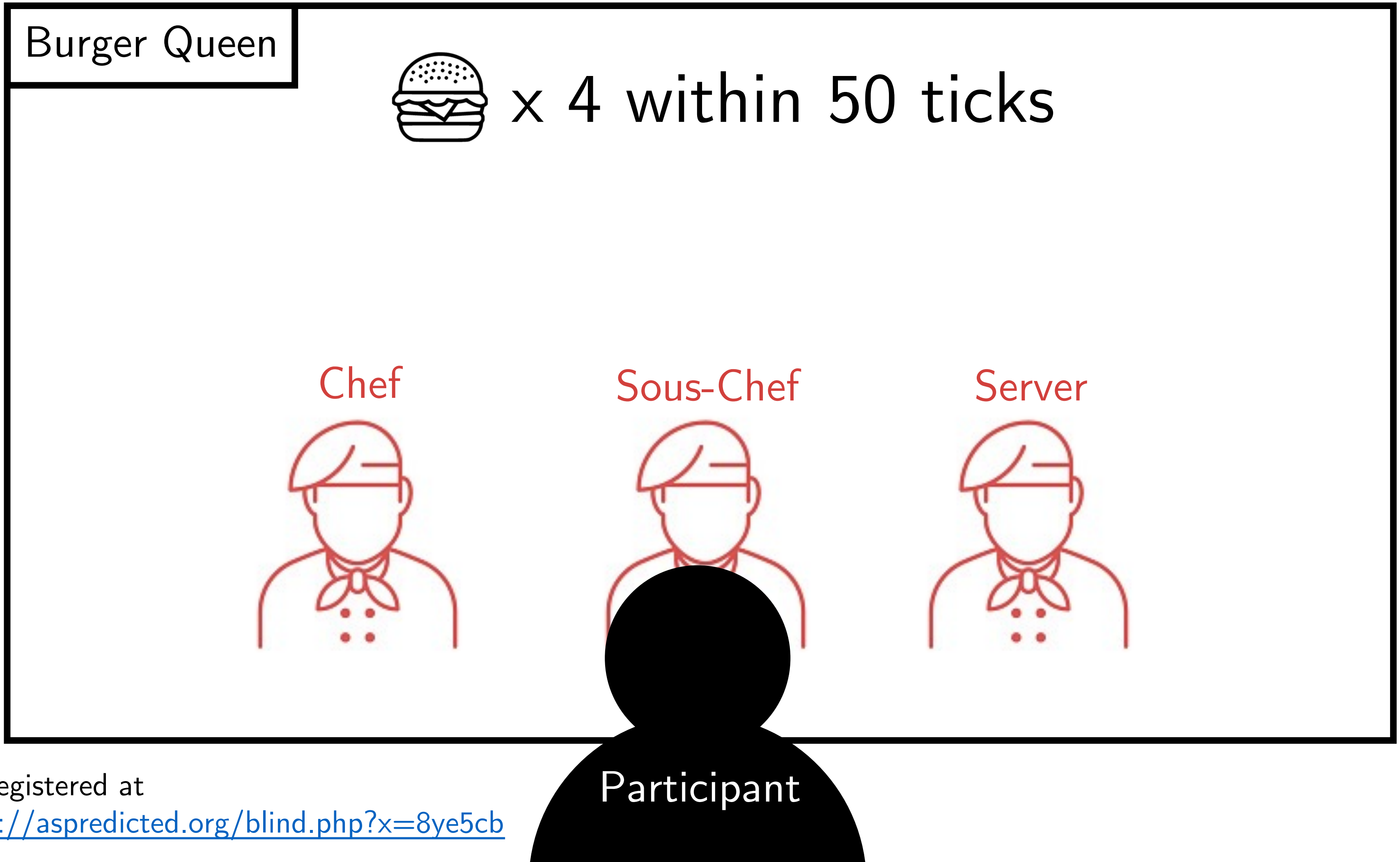

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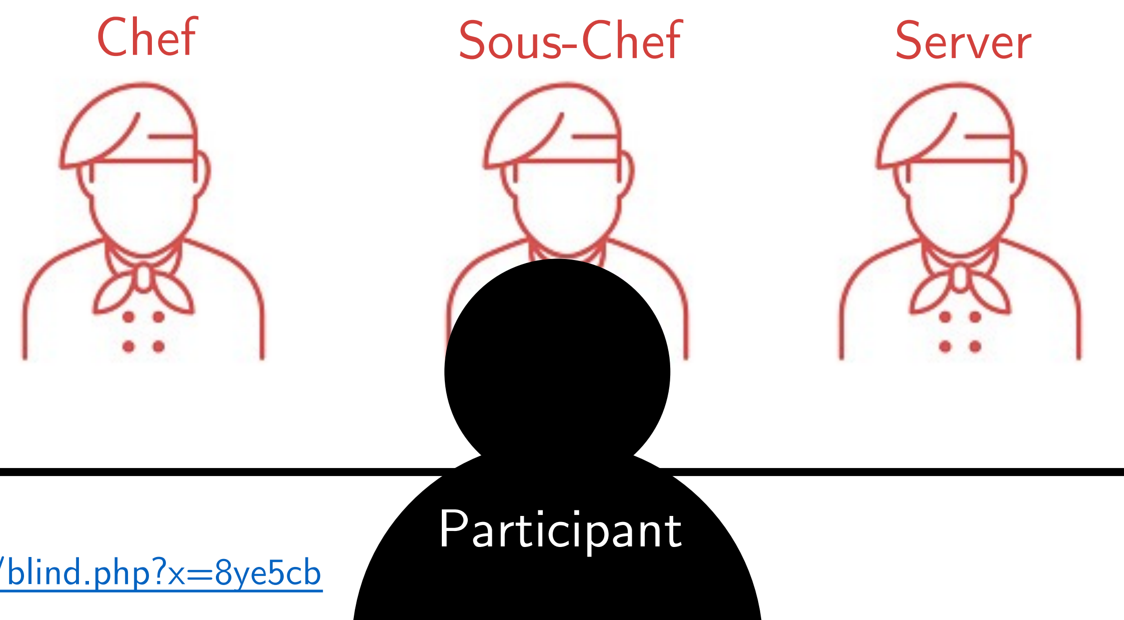
Study 1:

Cooking Game

Burger Queen

Chopping:	Fast	Average	Slow
Cooking:	Fast	Average	Slow
Plating:	Slow	Average	Fast



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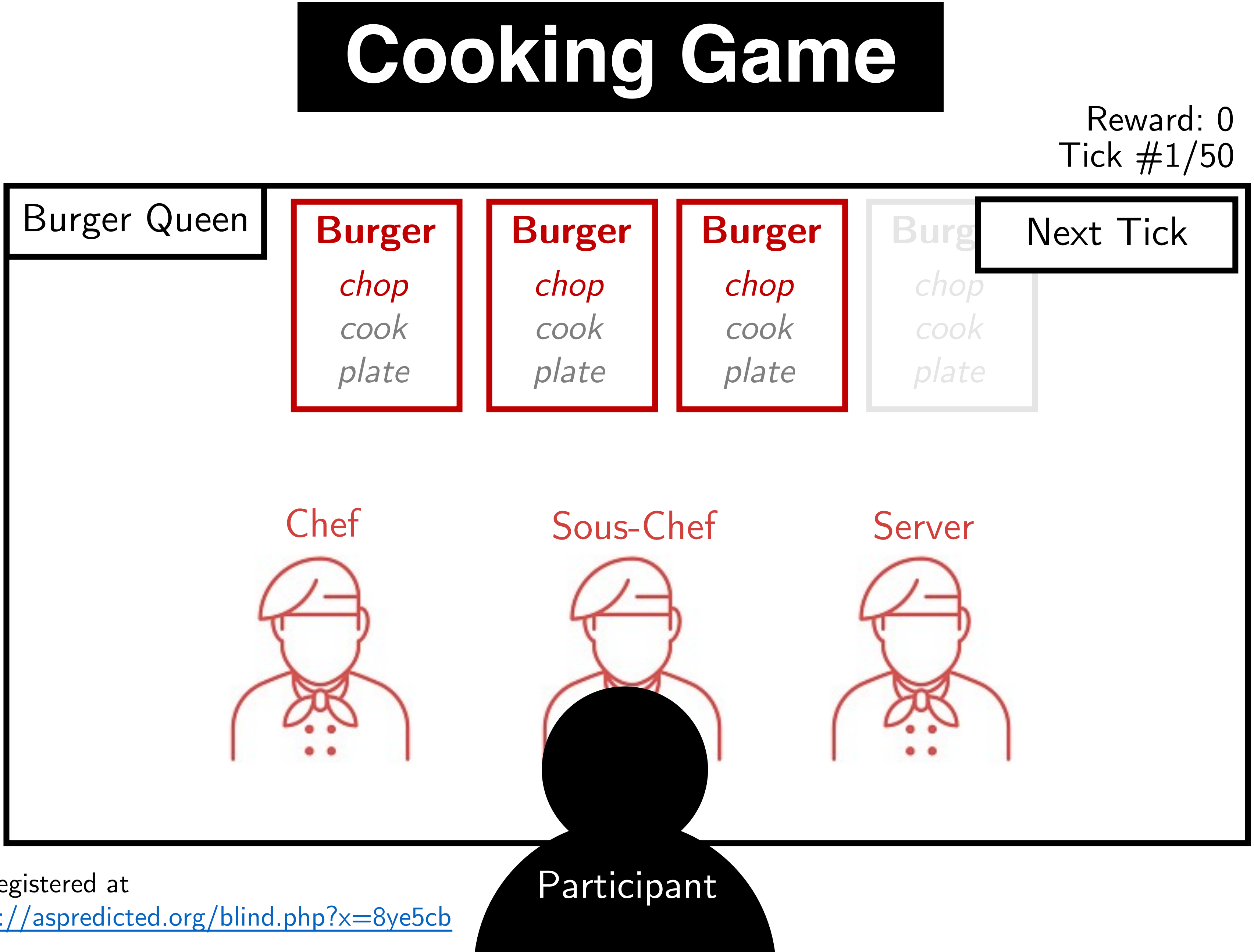

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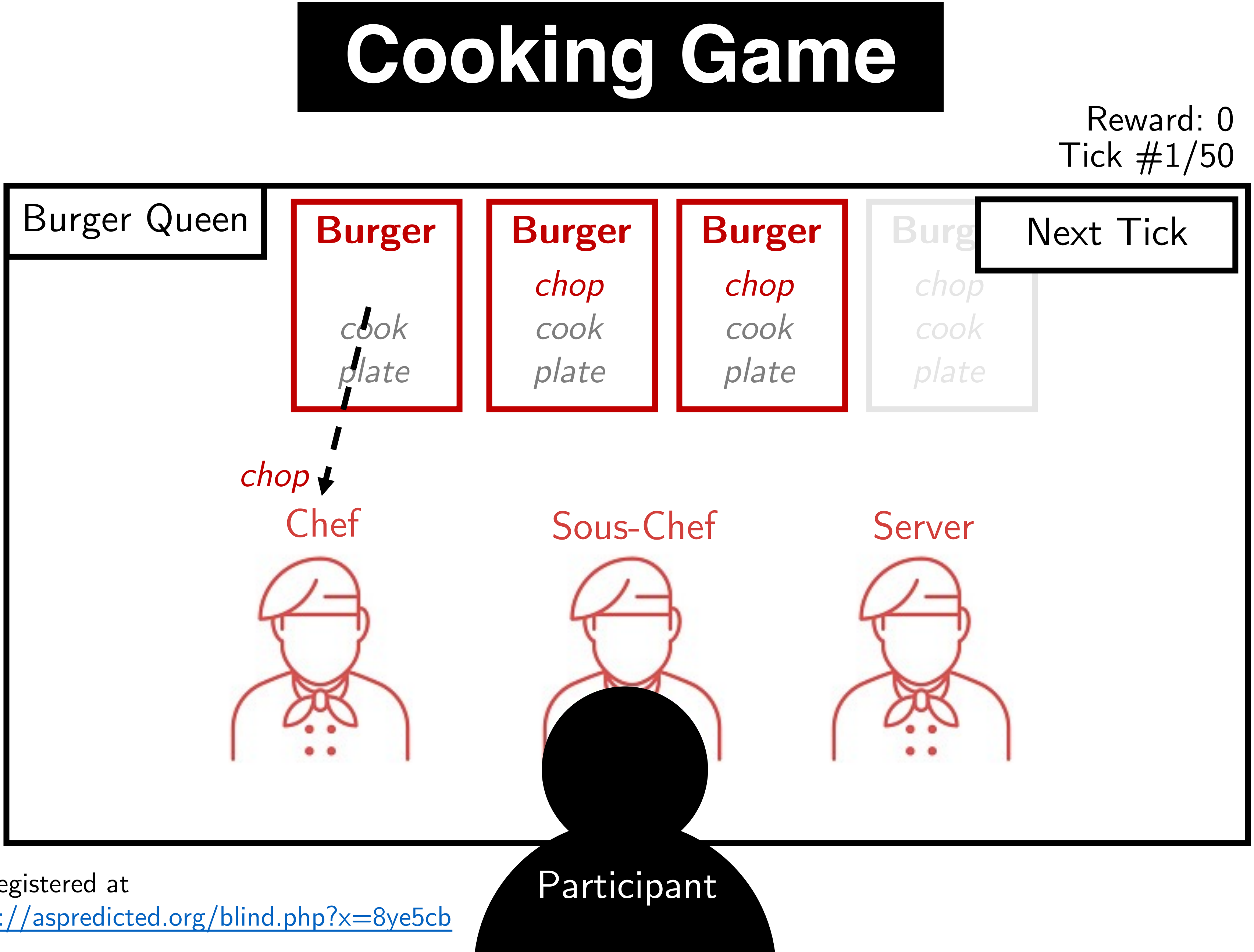

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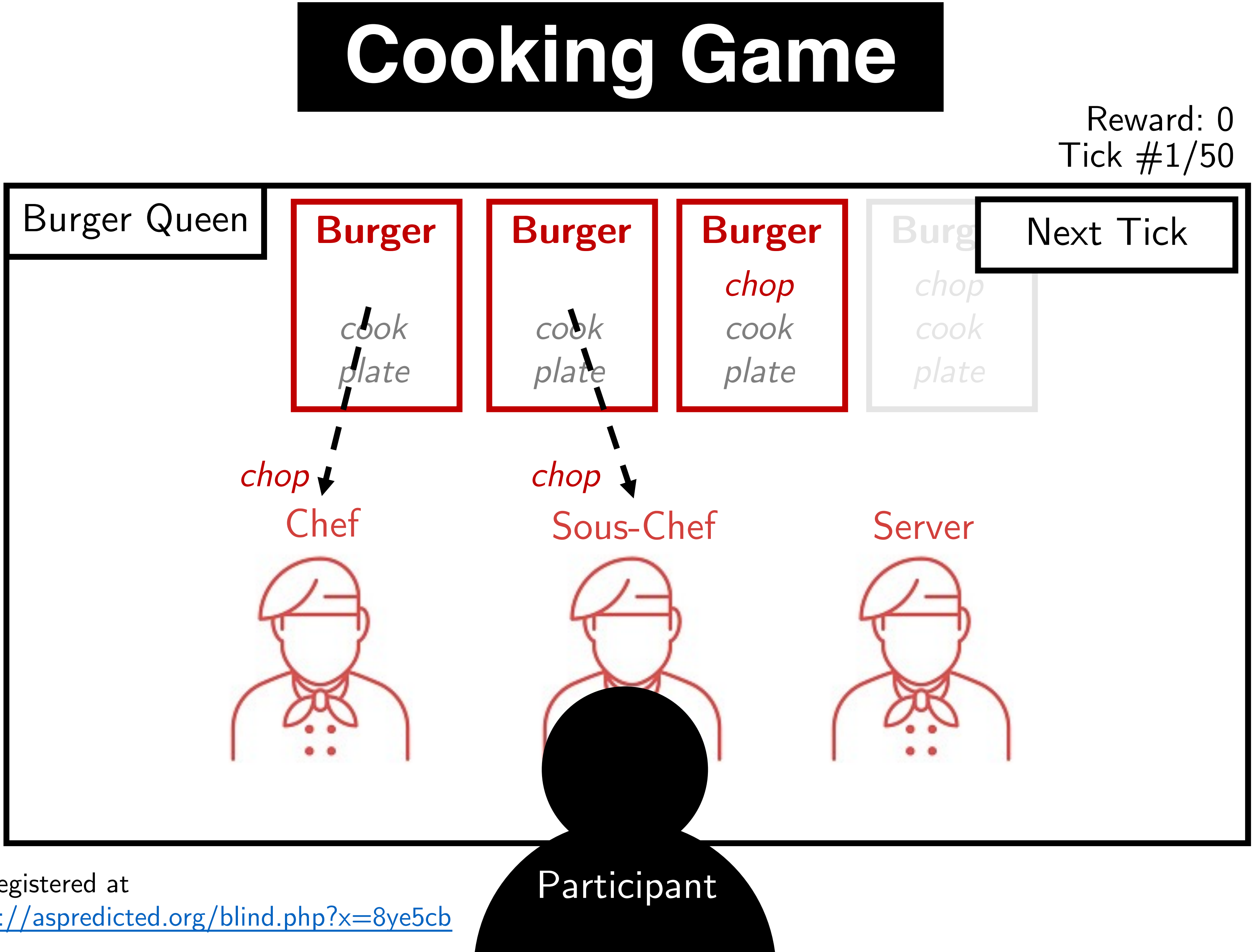

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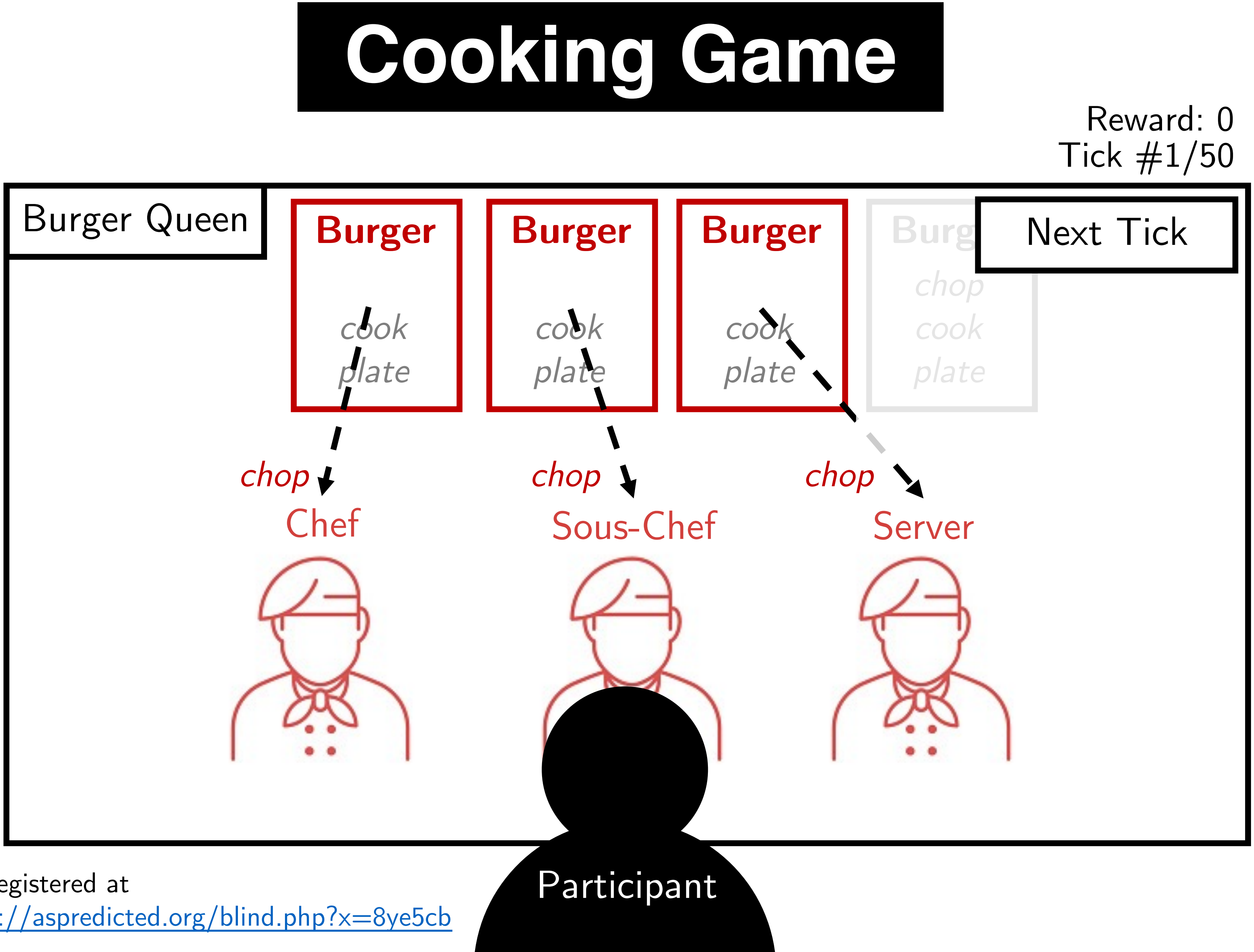

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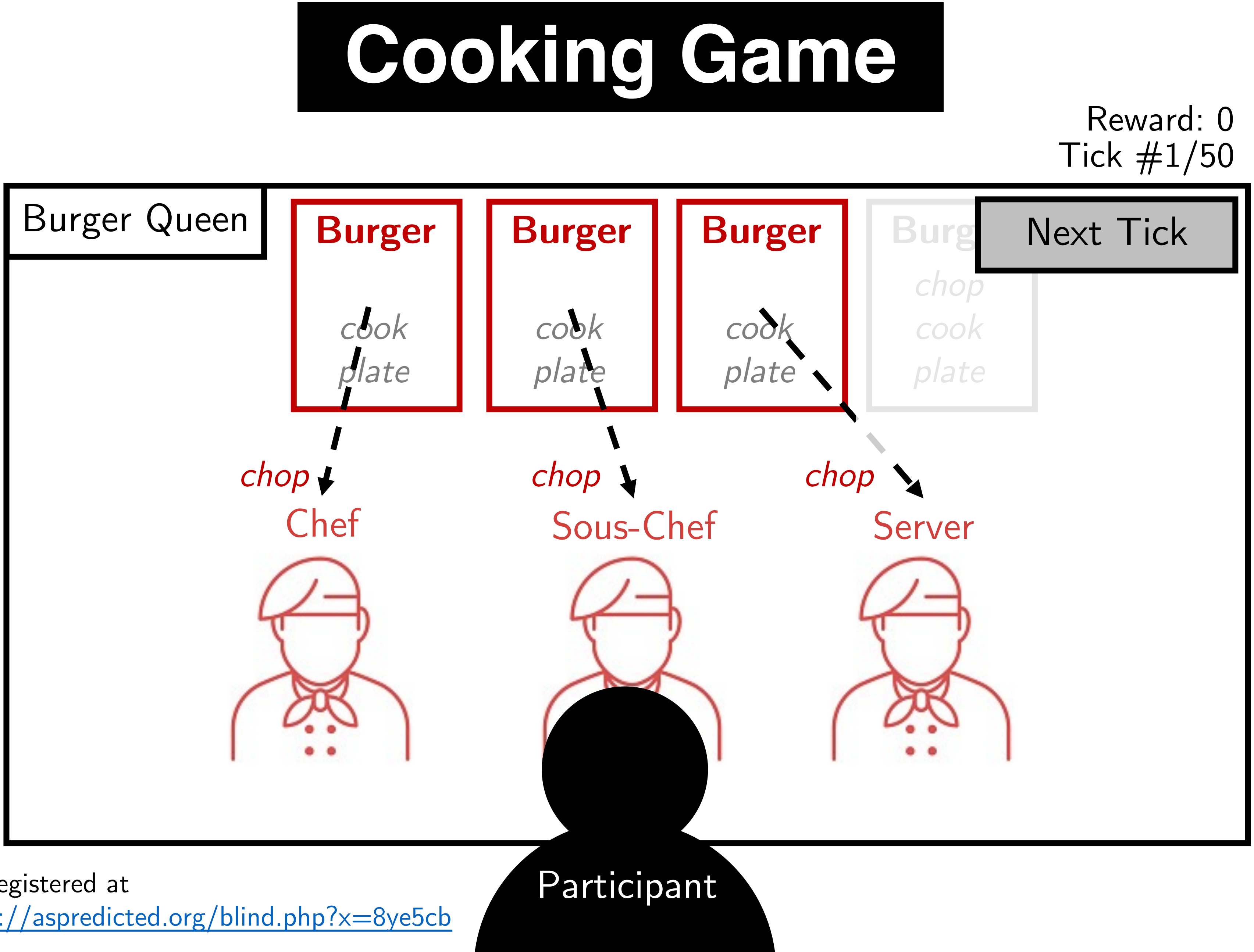

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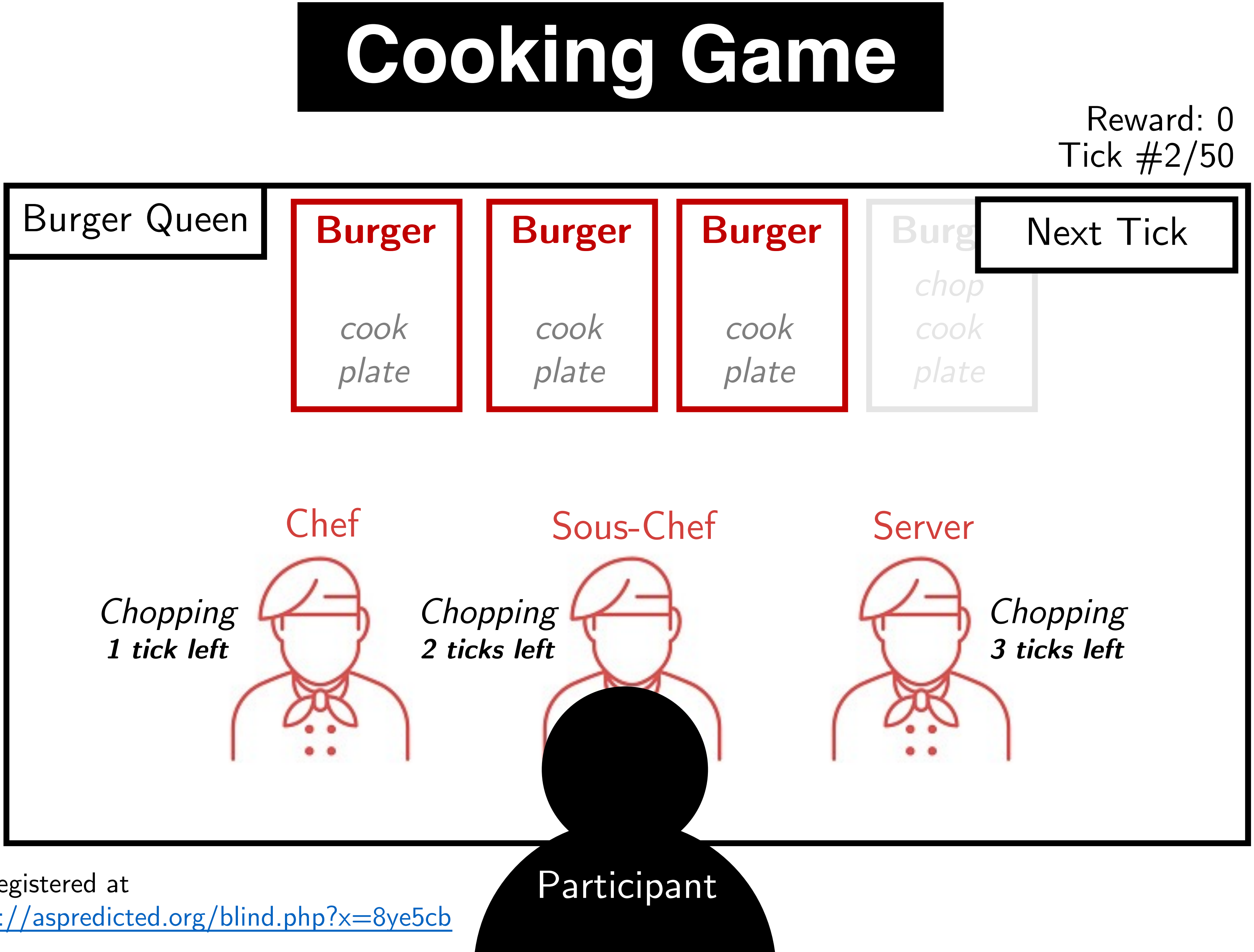

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Study 1:

Design

Disruption Scenario

🍔 x 4 within 50 ticks

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Design Disruption Scenario

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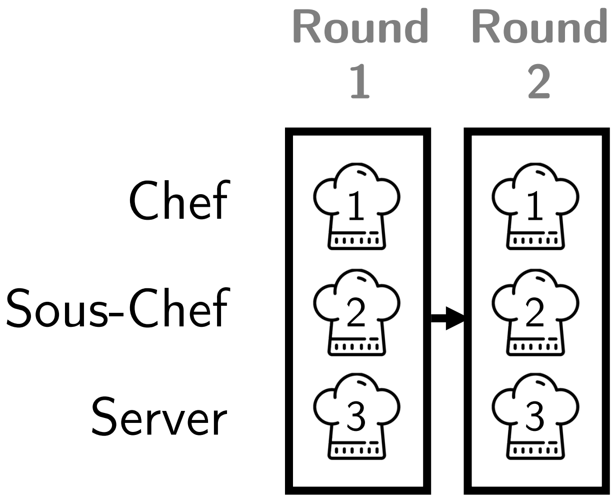

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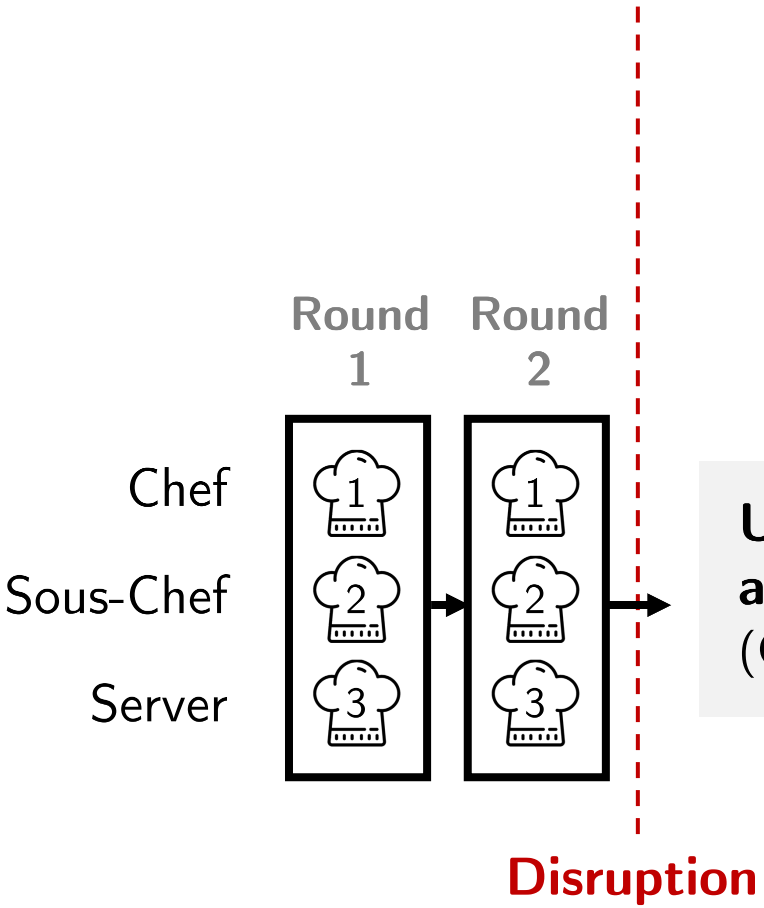

Unfortunately, the Chef is away training for Paris 2024.
(Good luck, Chef!)

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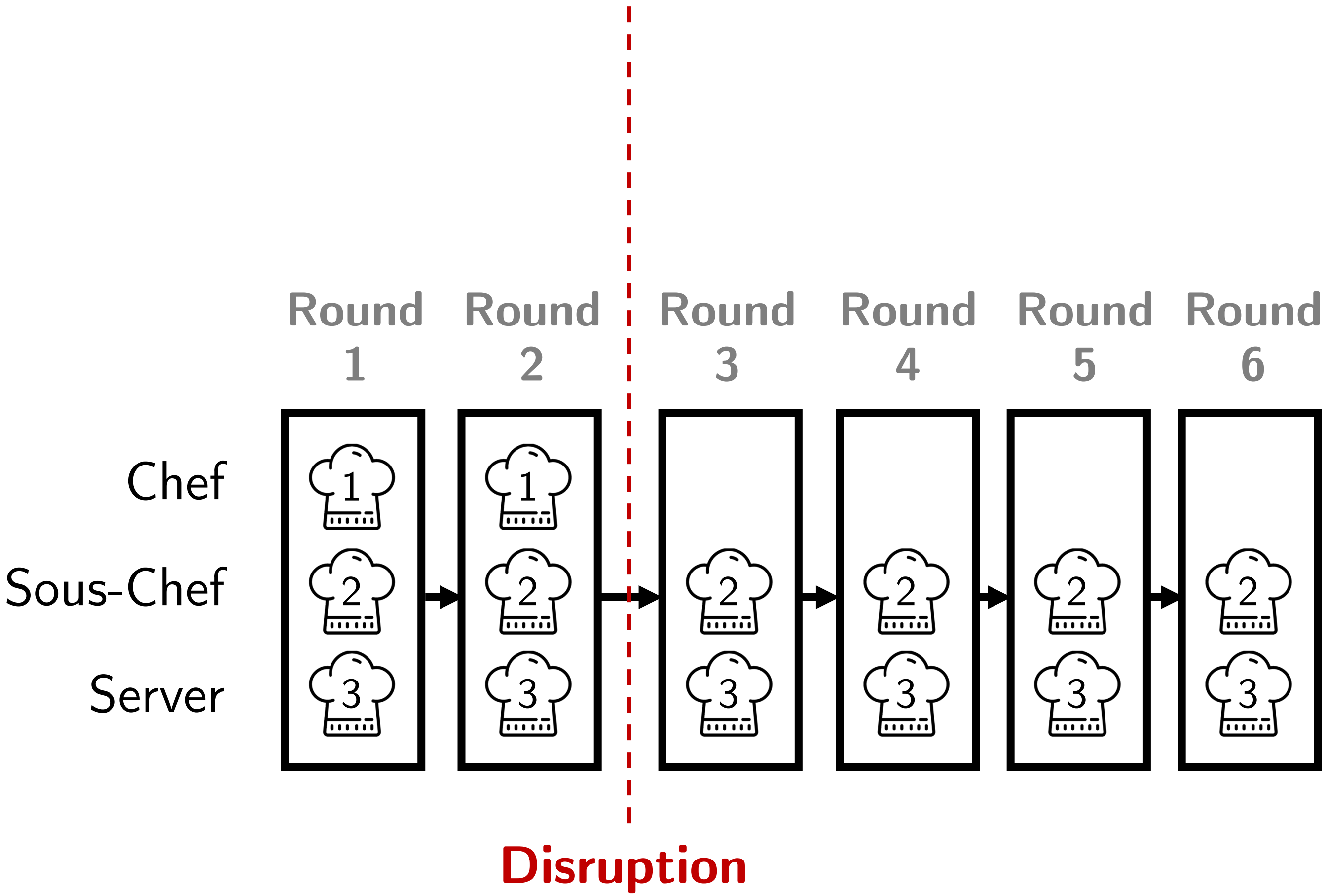
Design Disruption Scenario



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Problem Formulation

MDP Formulation:

Optimal policy and *human* make sequences of decisions

$$\mathcal{M} = (S, A, R, P, \gamma)$$

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π^* start s_1

π start s_1

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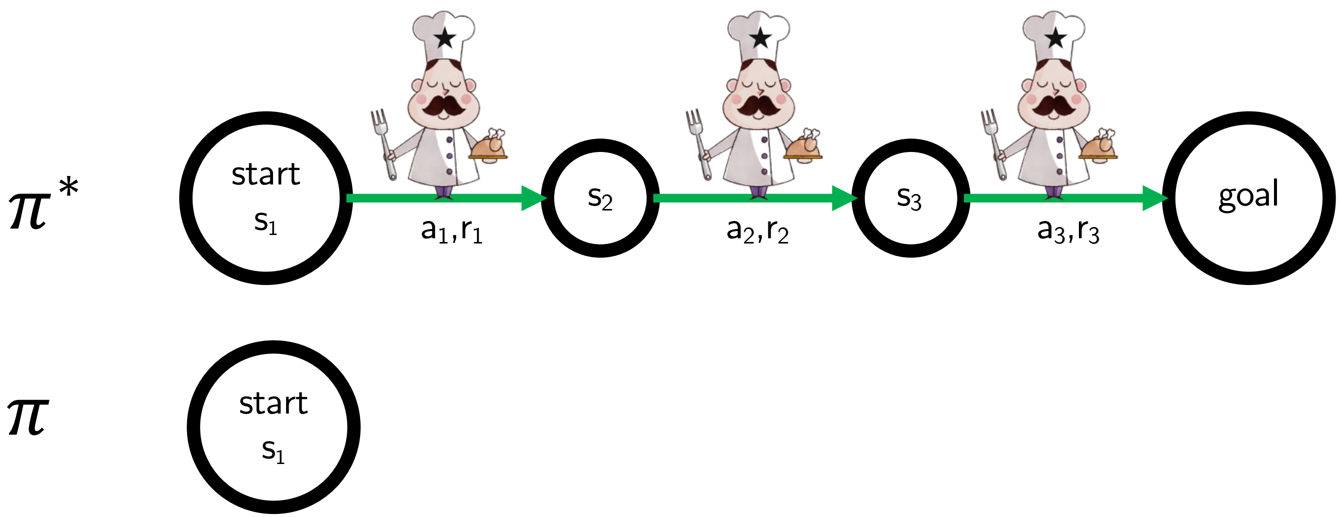

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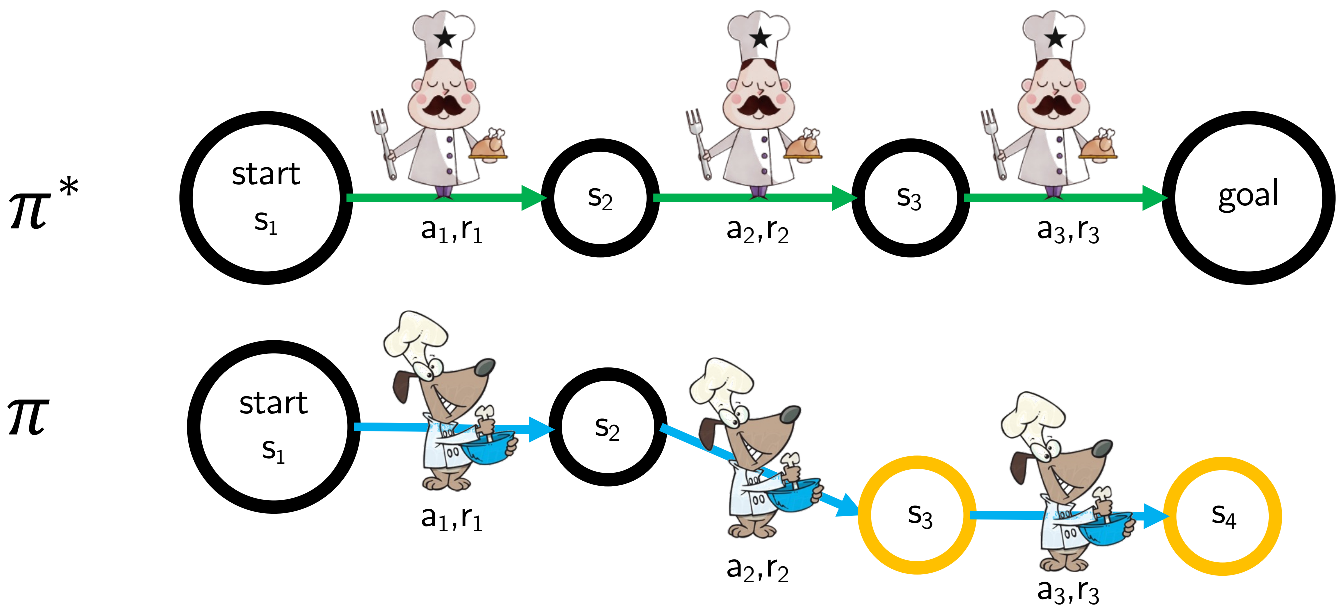
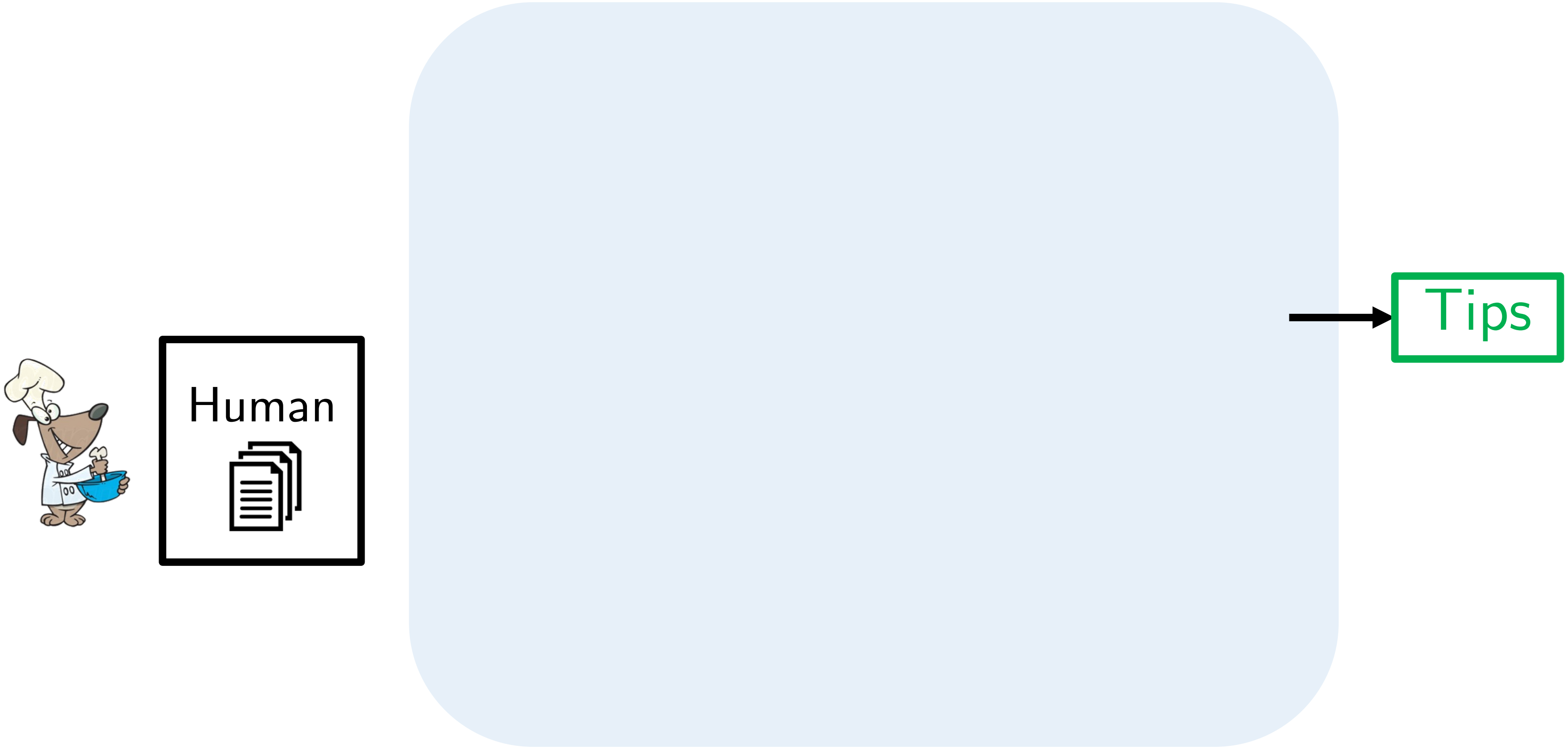


Our Approach



Our Approach

MDP: $\mathcal{M} = (S, A, R, P, \gamma)$

Human

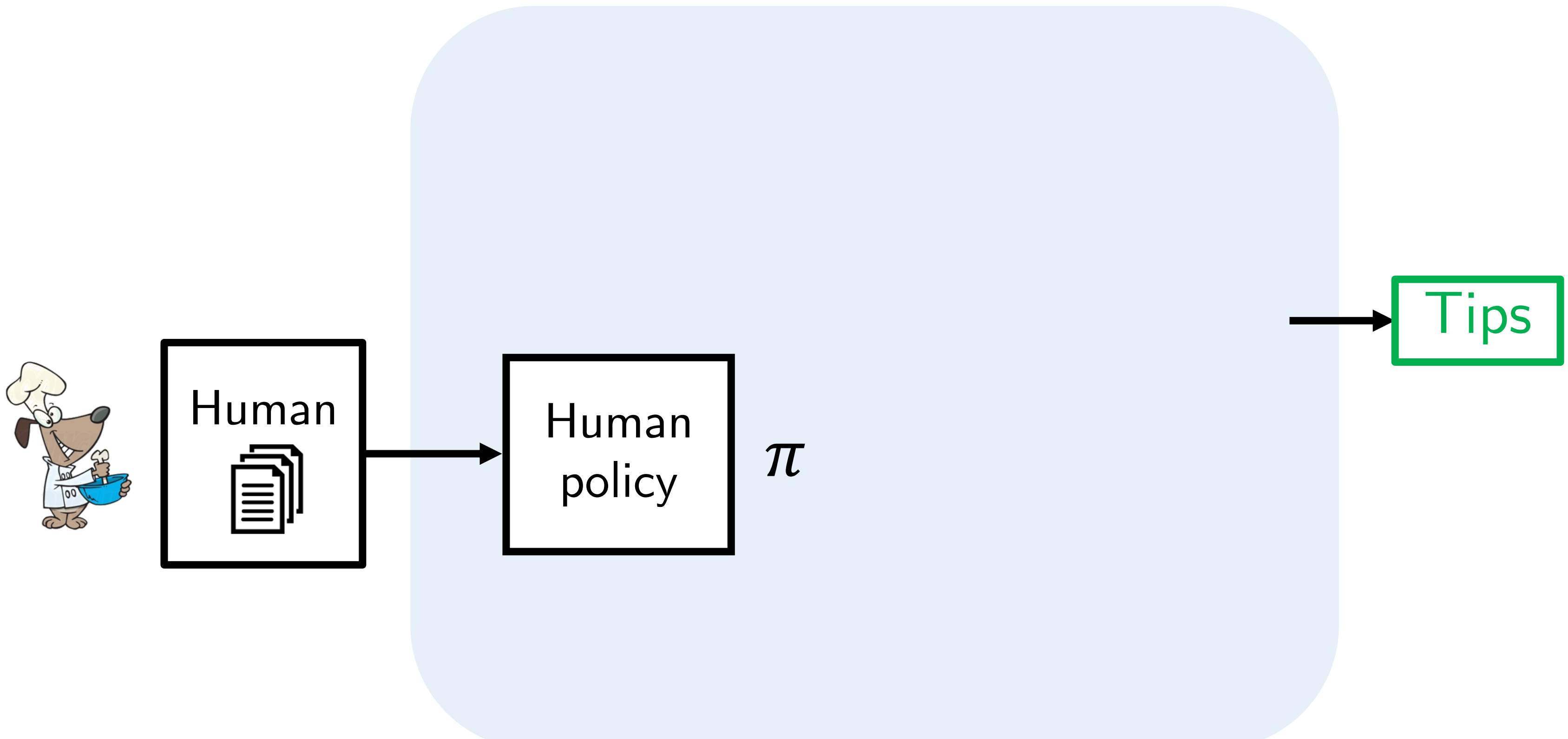
Input:
Trace data $\hat{d}_h$
from human

$\{(s_1, a_1, r_1), (s_2, a_2, r_2), \ldots, (s_T, a_T, r_T)\}$

Tips

Our Approach

MDP: $\mathcal{M} = (S, A, R, P, \gamma)$

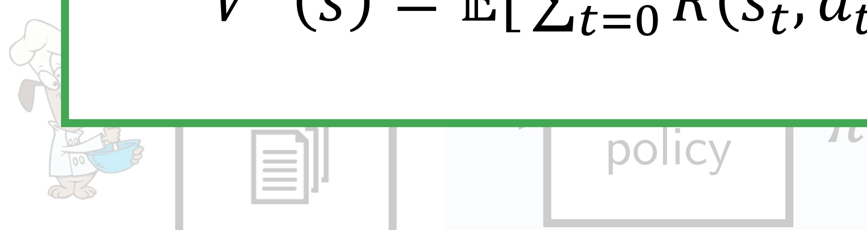


Our Approach

MDP: $\mathcal{M} = (S, A, R, P, \gamma)$

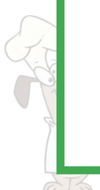
Value function $V^\pi(s)$ is the cumulative reward obtained by using policy π from state s

$$V^\pi(s) = \mathbb{E}[\,\sum_{t=0}^{T} R(s_t, a_t) \mid s_0 = s, a_t = \pi(s_t)\,]$$



Step 1: Q-Learning

MDP: $\mathcal{M} = (S, A, R, P, \gamma)$



Q function $Q^{\pi}(s, a)$ is the reward obtained by taking action a in state s and using policy π thereafter

$$Q^{\pi}(s, a) = \mathbb{E}_{s' \sim p(s'|s,a)}[V^{\pi}(s')]$$

- Watkins & Dayan 1992

Step 1: Q-Learning

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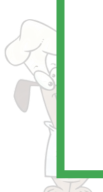

- Learn using supervised learning on trace data obtained using π

$$\hat{Q}^\pi_\theta(s,a) \approx Q^\pi(s,a)$$

Our Approach

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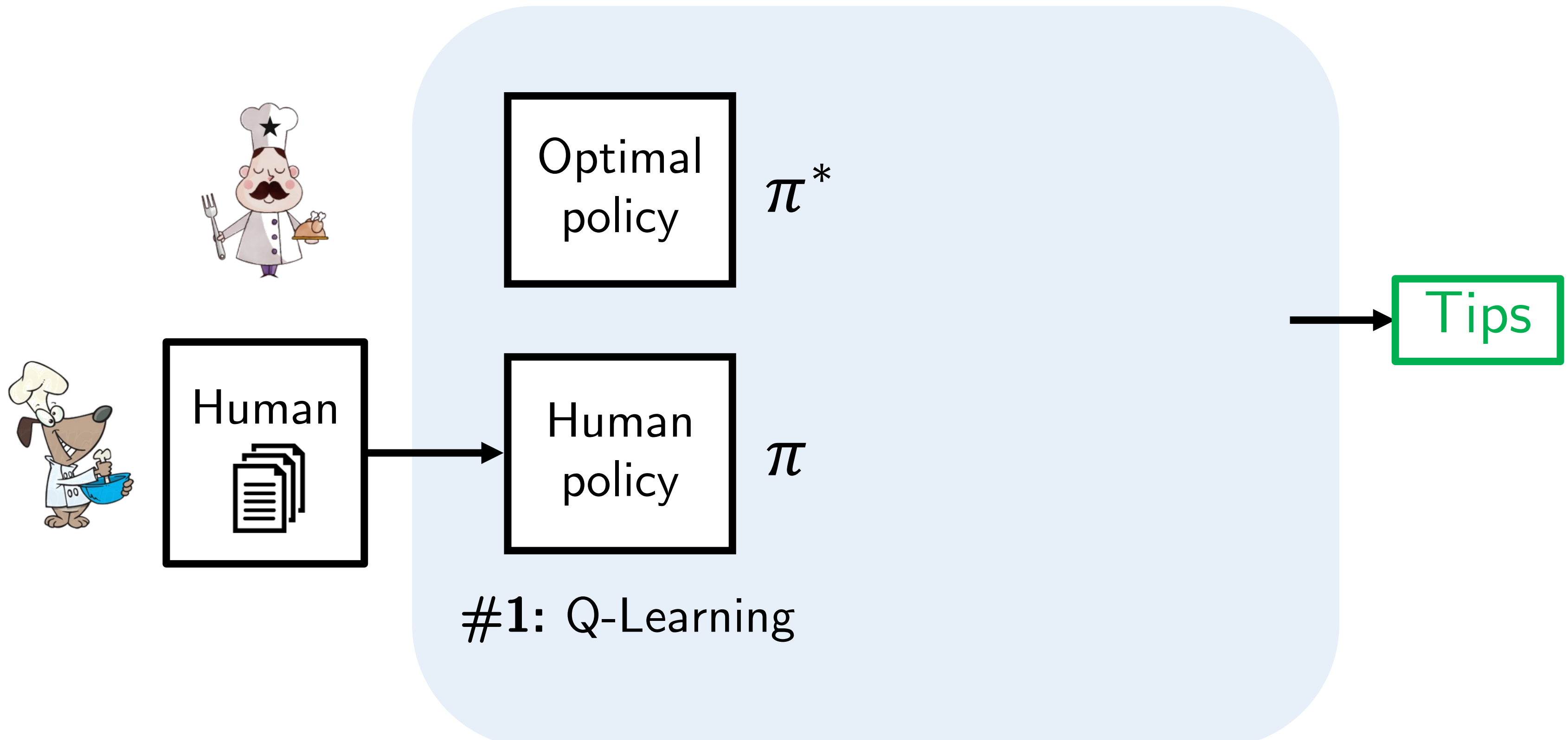

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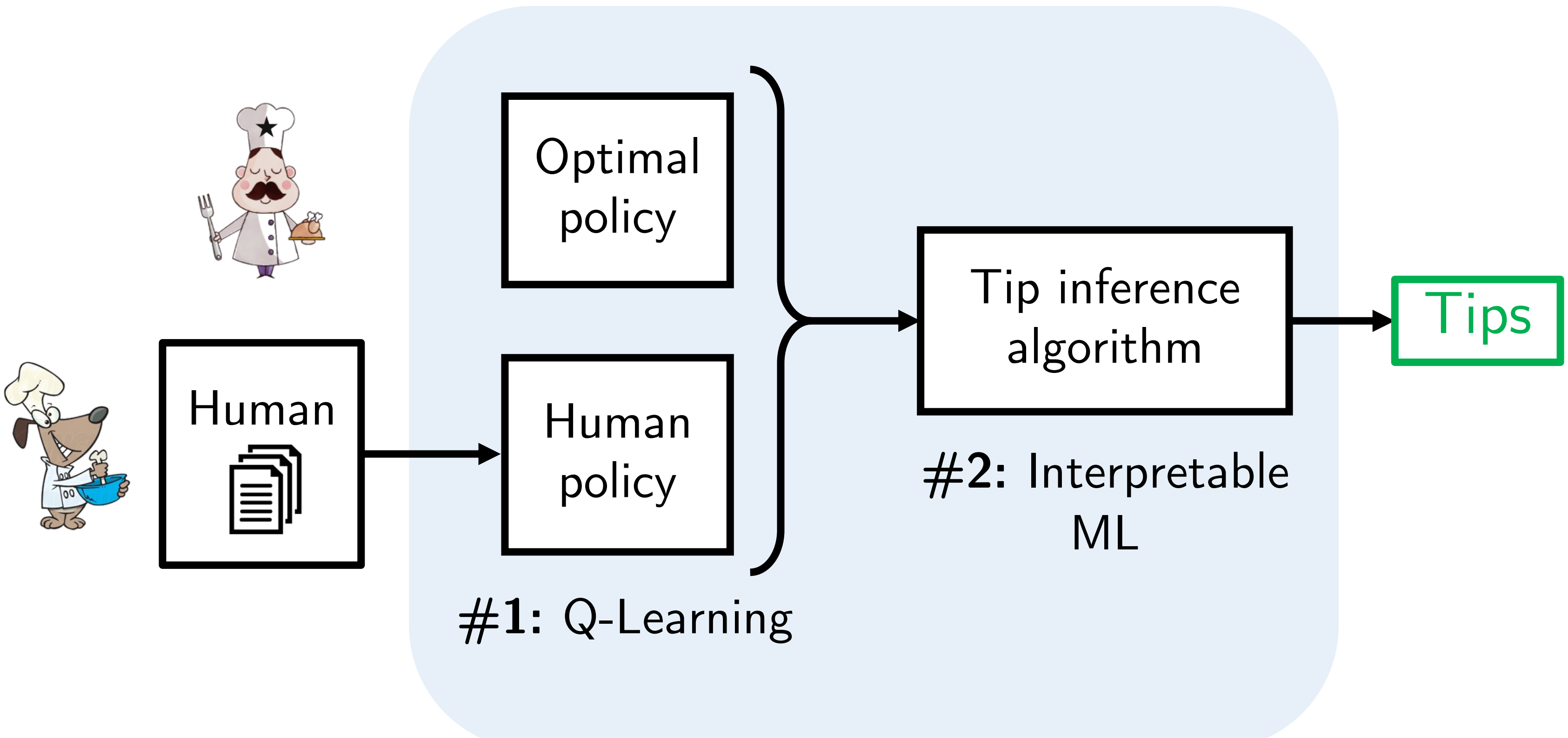

Caruana et al. 2015, Letham et al. 2015

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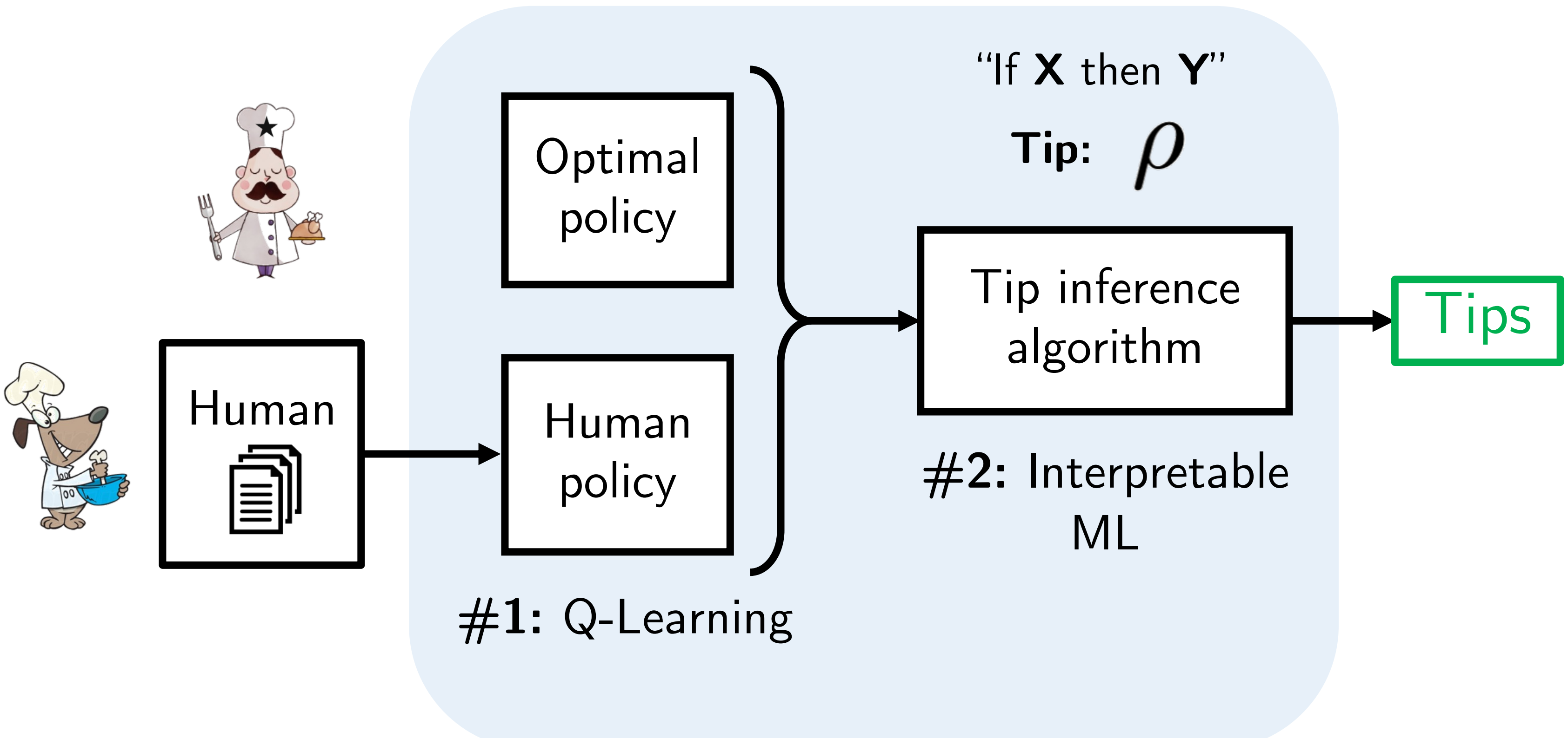

Caruana et al. 2015, Letham et al. 2015

Step 2: Tip Inference

Cumulative reward for a given policy

$$J(\pi) = \mathbb{E}_{\zeta \sim D(\pi)}\left[\sum_{t=1}^{T} r_t\right]$$

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Cumulative reward for a given policy

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- **Algorithm:** Choose tip ρ that maximizes the objective

$$J(\pi_H \oplus \rho) - J(\pi_H)$$

Human policy + tip **Only human policy**

- $\pi_{\mathrm{h}} \oplus \rho$ denotes overriding the human policy with tip ρ.

Step 2: Tip Inference

Cumulative reward for a given policy

$$J(\pi) = \mathbb{E}_{\zeta \sim D(\pi)}\left[\sum_{t=1}^{T} r_t\right]$$

- **Algorithm:** Choose tip ρ that maximizes the objective

$$\underbrace{J(\pi_H \oplus \rho)}_{\text{Human policy + tip}} - \underbrace{J(\pi_H)}_{\text{Only human policy}}$$

  - $\pi_{\mathrm{h}} \oplus \rho$ denotes overriding the human policy with tip ρ.

- **Lemma:** $J(\pi_H \oplus \rho) - J(\pi_H) \approx$

$$\mathbb{E}_{\zeta \sim D(\pi_H)}\left[\sum_{t=1}^{T} Q_t^*(s_t, \pi_H \oplus \rho(s_t)) - Q_t^*(s_t, \pi_H(s_t))\right]$$

Indirect effect of distribution shift is small; use observed data

Q-network we learned previously!

Step 2: Tip Inference

$$\text{if } (\text{order} = o \ \wedge \ \text{subtask} = s \ \wedge \ \text{virtual worker} = w) \text{ then } (\text{assign } (o, s) \text{ to } w),$$

If chopping for Burger #1 and chef are available,
then assign chopping Burger #1 to chef

Step 2: Tip Inference

$$\text{if } (\text{order} = o \;\wedge\; \text{subtask} = s \;\wedge\; \text{virtual worker} = w) \text{ then } (\text{assign } (o, s) \text{ to } w),$$

If chopping for Burger #1 and chef are available,
then assign chopping Burger #1 to chef

$$\text{if } (\text{order} = \text{burger}_1 \;\wedge\; \text{subtask} = \text{cooking} \;\wedge\; \text{virtual worker} = \text{chef}) \text{ then } (\text{assign } (\text{burger}_1, \text{cooking}) \text{ to chef}),$$

$$\text{if } (\text{order} = \text{burger}_2 \;\wedge\; \text{subtask} = \text{cooking} \;\wedge\; \text{virtual worker} = \text{chef}) \text{ then } (\text{assign } (\text{burger}_2, \text{cooking}) \text{ to chef}),$$

Step 2: Tip Inference

$$\text{if } (\text{order} = o \ \wedge \ \text{subtask} = s \ \wedge \ \text{virtual worker} = w) \text{ then } (\text{assign } (o, s) \text{ to } w),$$

If chopping for Burger #1 and chef are available,
then assign chopping Burger #1 to chef

$$\text{if } (\text{order} = \text{burger}_1 \ \wedge \ \text{subtask} = \text{cooking} \ \wedge \ \text{virtual worker} = \text{chef}) \text{ then } (\text{assign } (\text{burger}_1, \text{cooking}) \text{ to chef}),$$

$$\text{if } (\text{order} = \text{burger}_2 \ \wedge \ \text{subtask} = \text{cooking} \ \wedge \ \text{virtual worker} = \text{chef}) \text{ then } (\text{assign } (\text{burger}_2, \text{cooking}) \text{ to chef}),$$

$$\downarrow$$

Assign chef to cook the first 2 burgers

Step 2: Tip Inference

$$\text{if (order} = o \ \wedge \ \text{subtask} = s \ \wedge \ \text{virtual worker} = w) \text{ then (assign } (o, s) \text{ to } w),$$

If chopping for Burger #1 and chef are available,
then assign chopping Burger #1 to chef

$$\text{if (order} = \text{burger}_1 \ \wedge \ \text{subtask} = \text{cooking} \ \wedge \ \text{virtual worker} = \text{chef) then (assign (burger}_1, \text{cooking) to chef)},$$

$$\text{if (order} = \text{burger}_2 \ \wedge \ \text{subtask} = \text{cooking} \ \wedge \ \text{virtual worker} = \text{chef) then (assign (burger}_2, \text{cooking) to chef)},$$

$\downarrow$

Assign chef to cook the first 2 burgers

$\downarrow$

Chef should cook twice

Step 2: Tip Inference

$$\text{if (order} = o \ \wedge\ \text{subtask} = s \ \wedge\ \text{virtual worker} = w) \text{ then (assign } (o, s) \text{ to } w),$$

If chopping for Burger #1 and chef are available,
then assign chopping Burger #1 to chef

$$\text{if (order} = \text{burger}_1 \ \wedge\ \text{subtask} = \text{cooking} \ \wedge\ \text{virtual worker} = \text{chef}) \text{ then (assign } (\text{burger}_1, \text{cooking}) \text{ to chef}),$$

$$\text{if (order} = \text{burger}_2 \ \wedge\ \text{subtask} = \text{cooking} \ \wedge\ \text{virtual worker} = \text{chef}) \text{ then (assign } (\text{burger}_2, \text{cooking}) \text{ to chef}),$$

↓

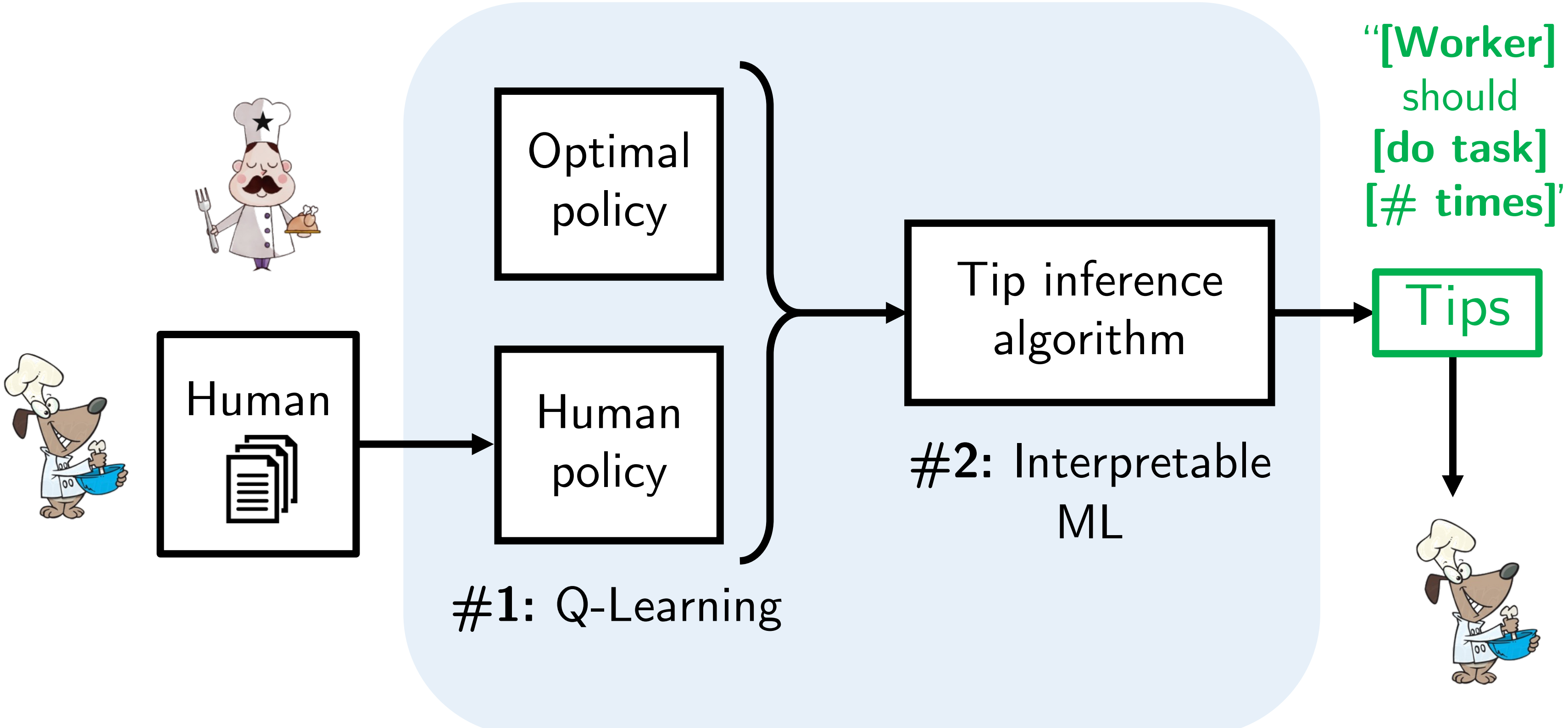
Assign chef to cook the first 2 burgers

↓

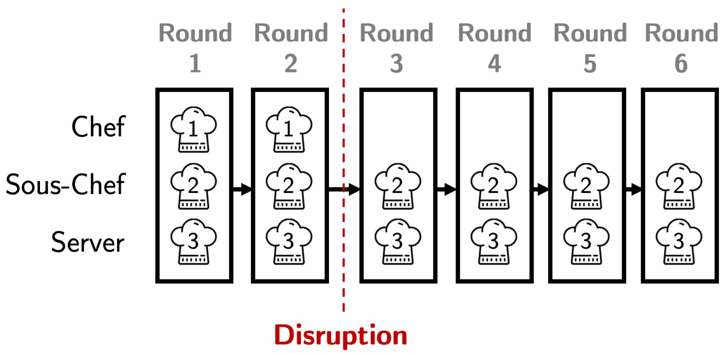
Chef should cook twice

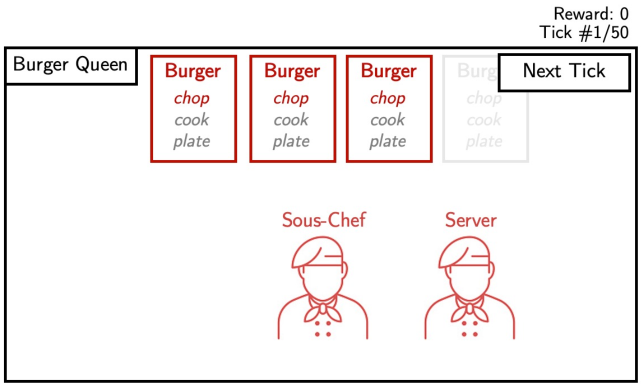
"**[Worker]** should **[do task]** **[# times]**"

Our Approach



Phase I Collect Trace Data

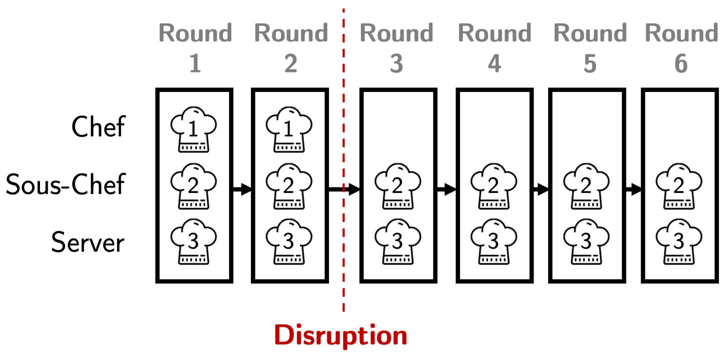


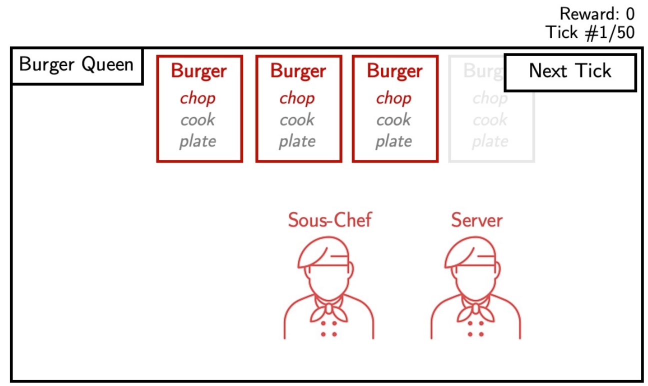


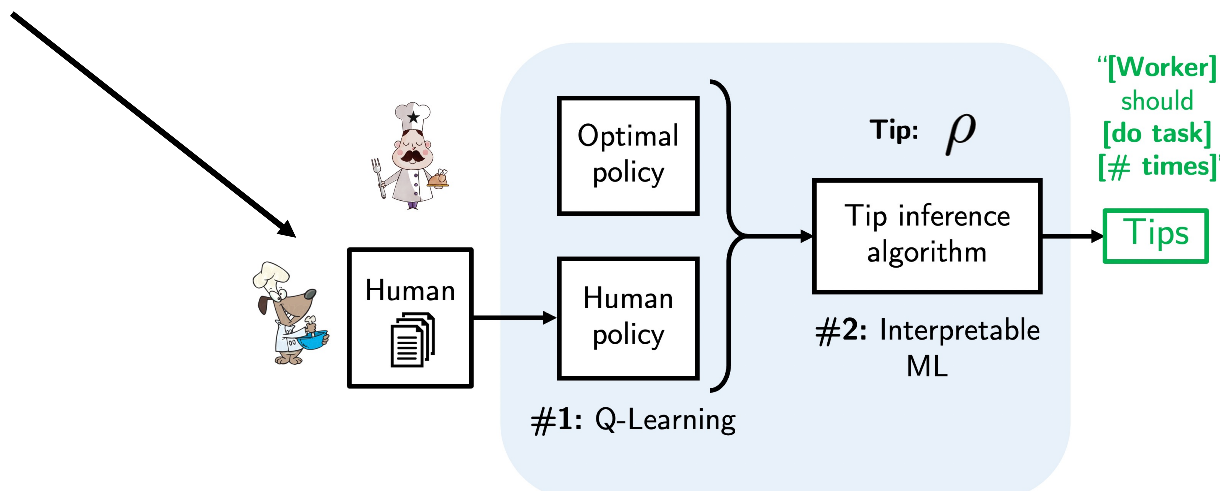
Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female

Phase I Collect Trace Data







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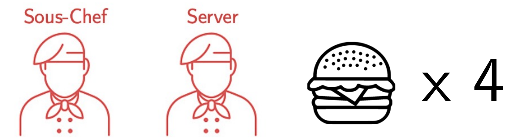
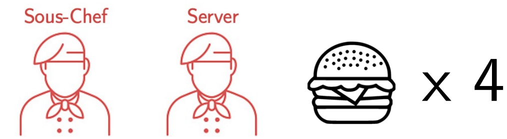


Phase I Inferred Tips

Algorithm

Server
should cook twice

Amazon Mechanical Turk, N = 172
mean age 36.4, 62% female



Phase I Inferred Tips

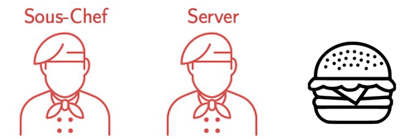
Algorithm

Human

Server
should cook twice

*Most frequent tip
chosen by participants*

Amazon Mechanical Turk, N = 172
mean age 36.4, 62% female



x 4

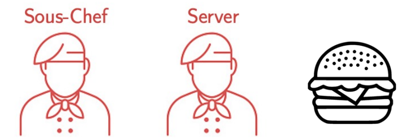
Phase I Inferred Tips

Algorithm	Human
Server should cook twice	Server should cook once

Most frequent tip chosen by participants

Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female



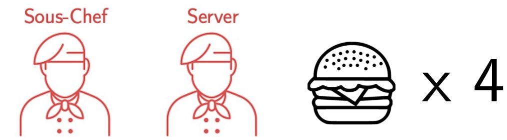
x 4

Phase I Inferred Tips

Algorithm	Human	Baseline
Server should cook twice	Server should cook once	
	Most frequent tip chosen by participants	
		Most frequent s-a deviation b/w optimal and trainee policies

Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female



Phase I Inferred Tips

Algorithm	Human	Baseline
Server should cook twice	Server should cook once	Sous-Chef should plate twice
	Most frequent tip chosen by participants	
		Most frequent s-a deviation b/w optimal and trainee policies

Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female

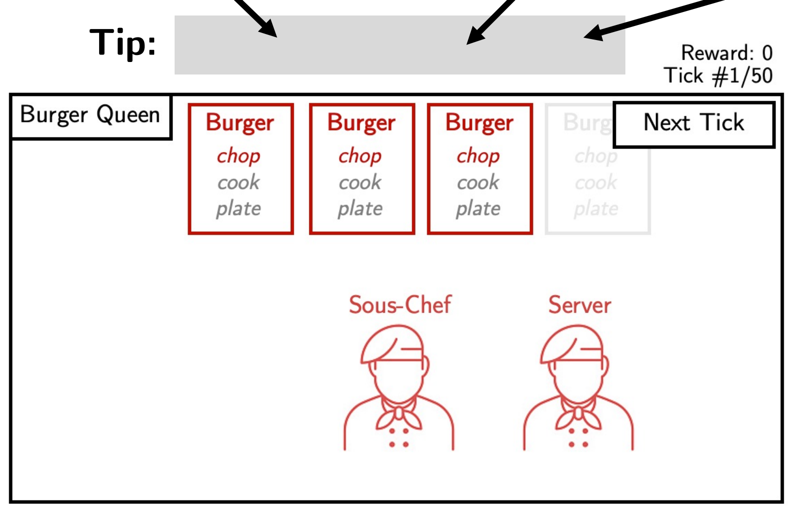
Phase II Comparing Tips

Control	Algorithm	Human	Baseline
- No tip -	Server should cook twice	Server should cook once	Sous-Chef should plate twice

Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Phase II Comparing Tips

Control	Algorithm	Human	Baseline
- No tip -	Server should cook twice	Server should cook once	Sous-Chef should plate twice



Amazon Mechanical Turk, N = 1,011

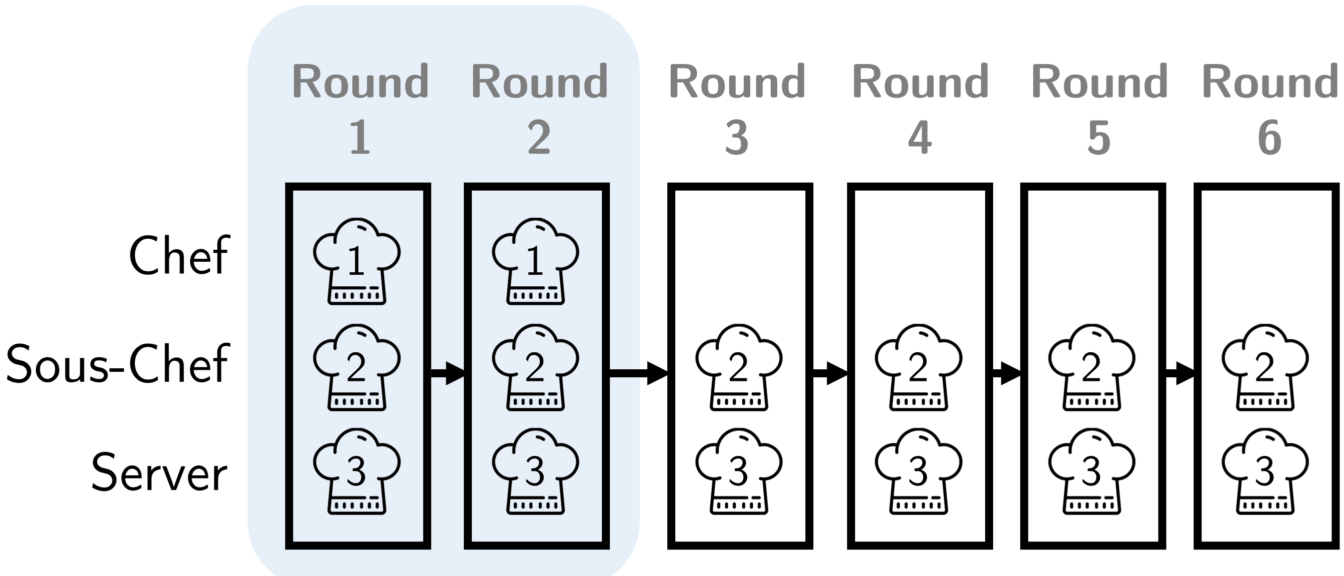
mean age 34.9, 60% female

Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once

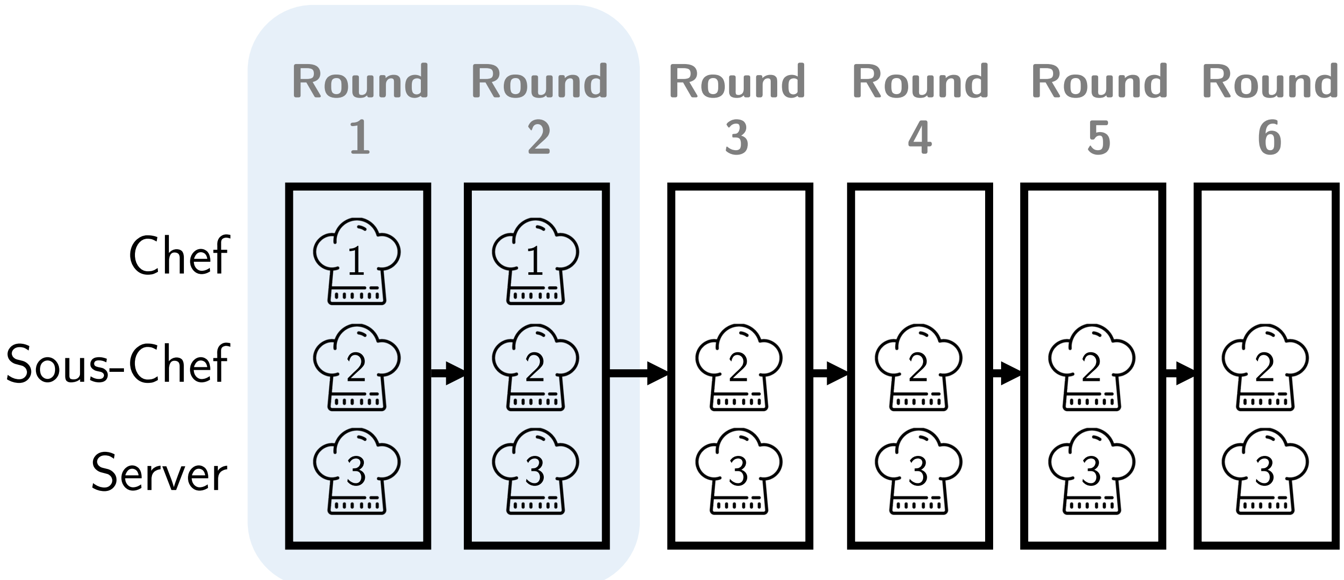
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



Algorithm vs Human

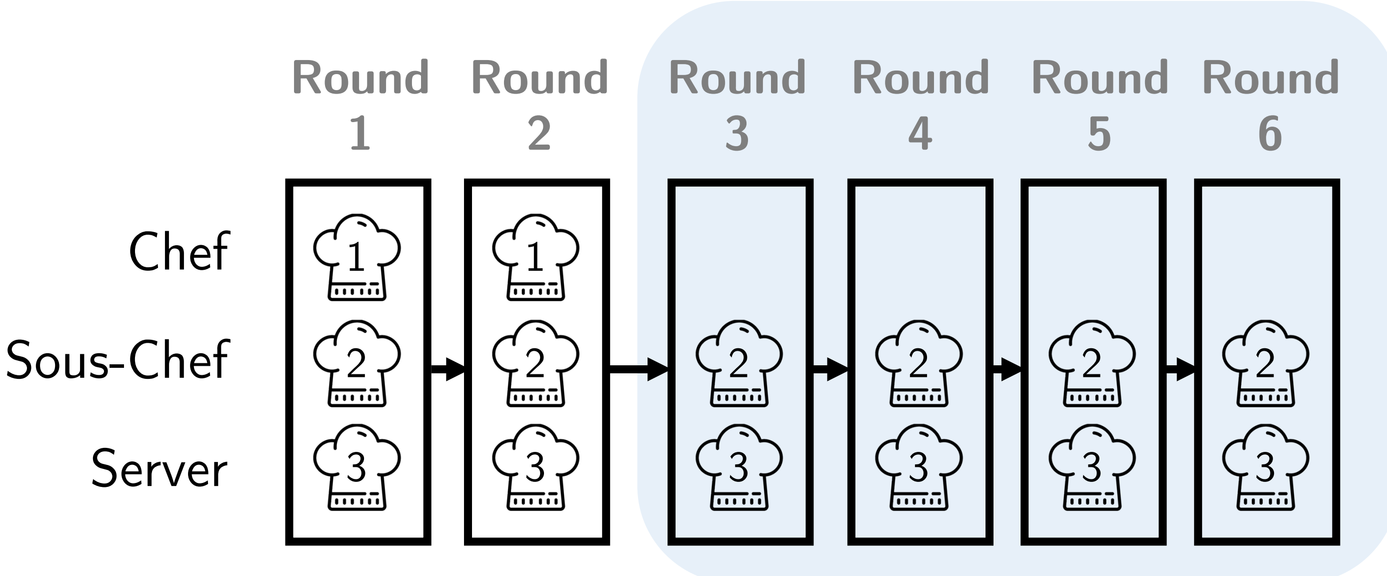
Algorithm	Human
Server should cook twice	Server should cook once



"Server shouldn't cook"

Algorithm vs Human

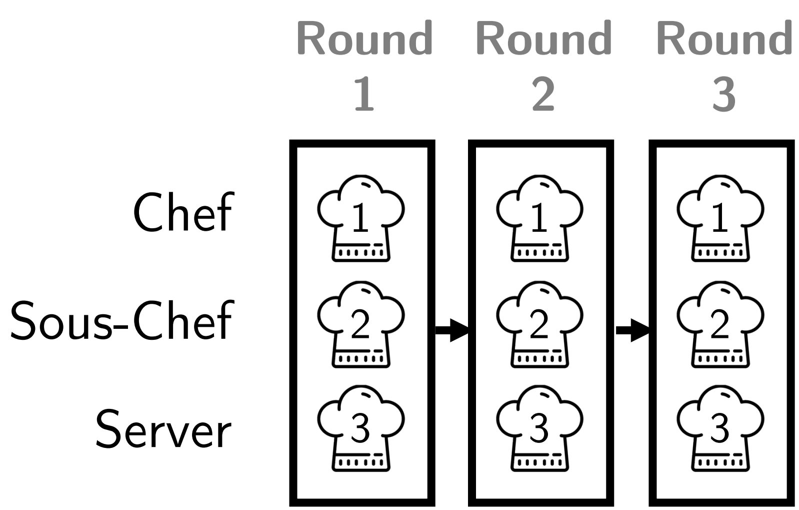
Algorithm	Human
Server should cook twice	Server should cook once



"Server shouldn't cook"

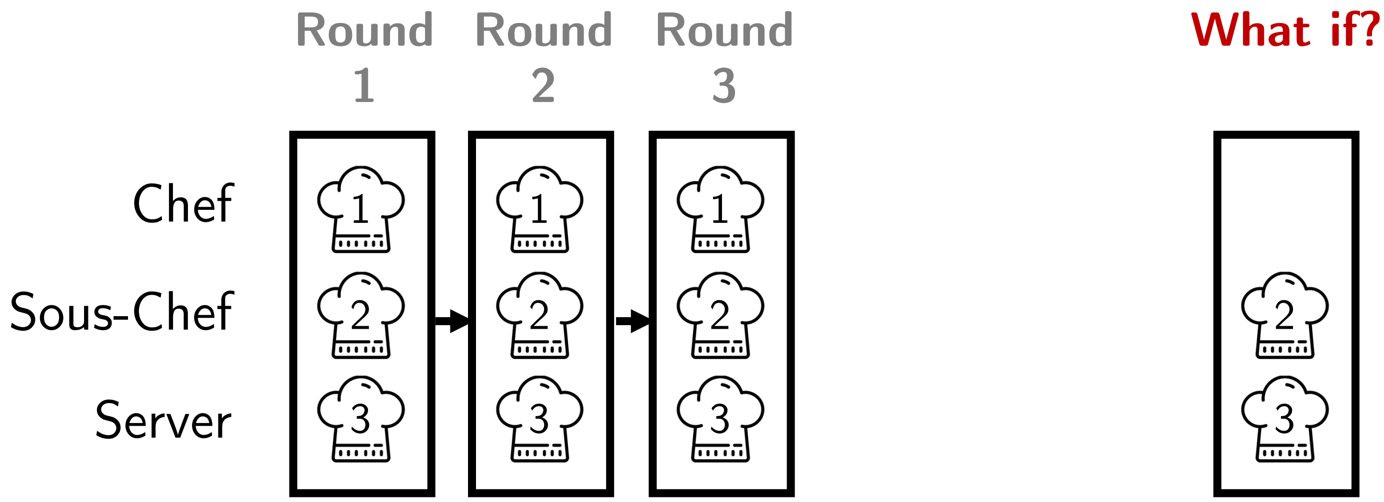
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



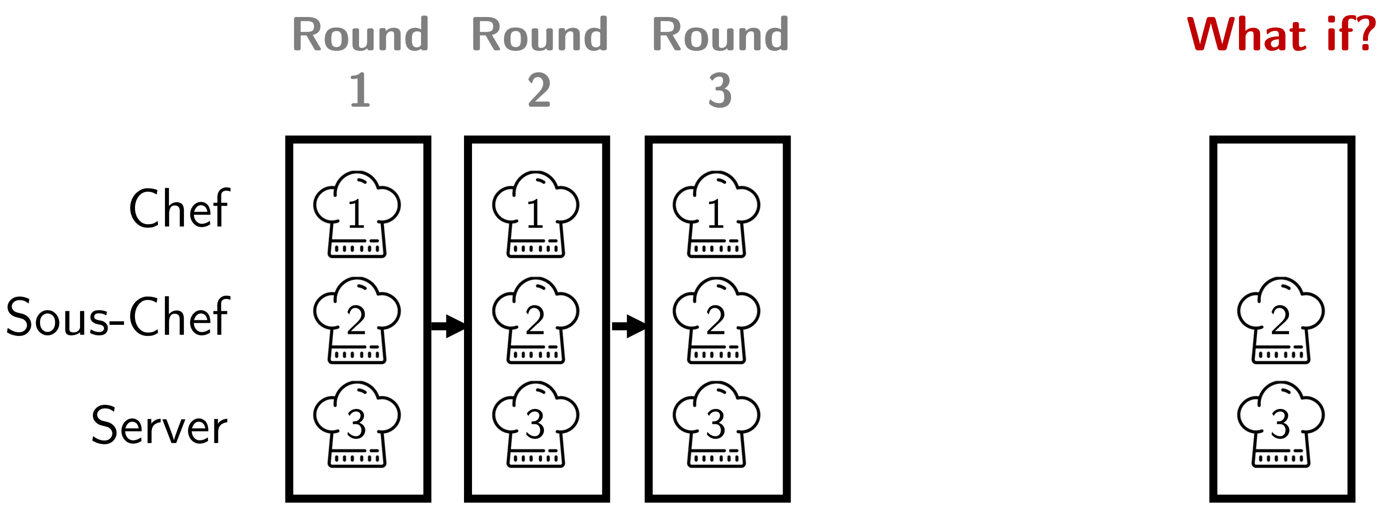
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



Algorithm vs Human

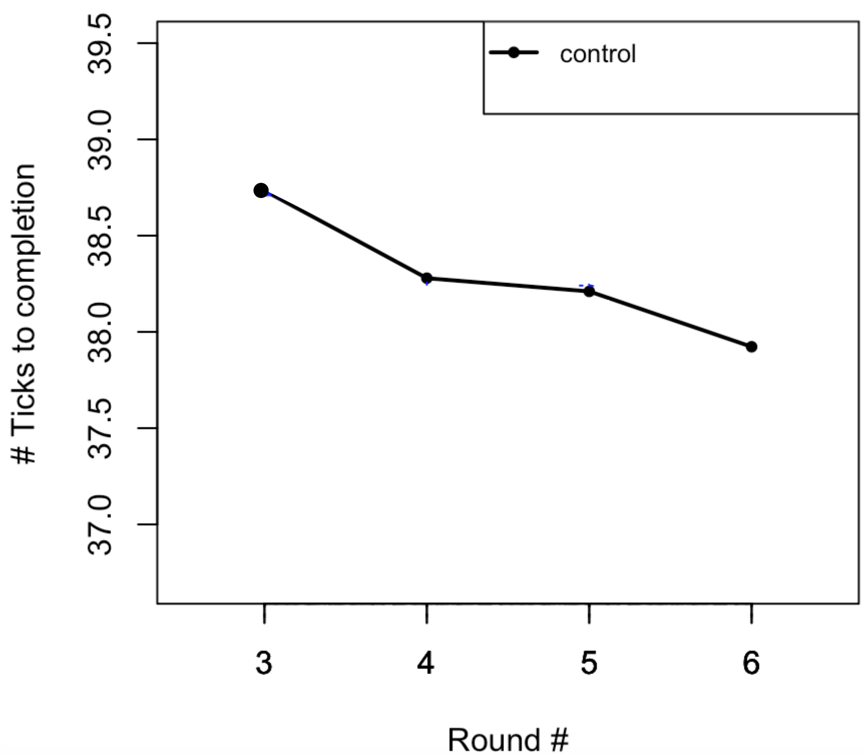
Algorithm	Human	Hypothetical
Server should cook twice	Server should cook once	Server shouldn't cook



Study 1:

Results People Improve Over Time

Ticks to completion



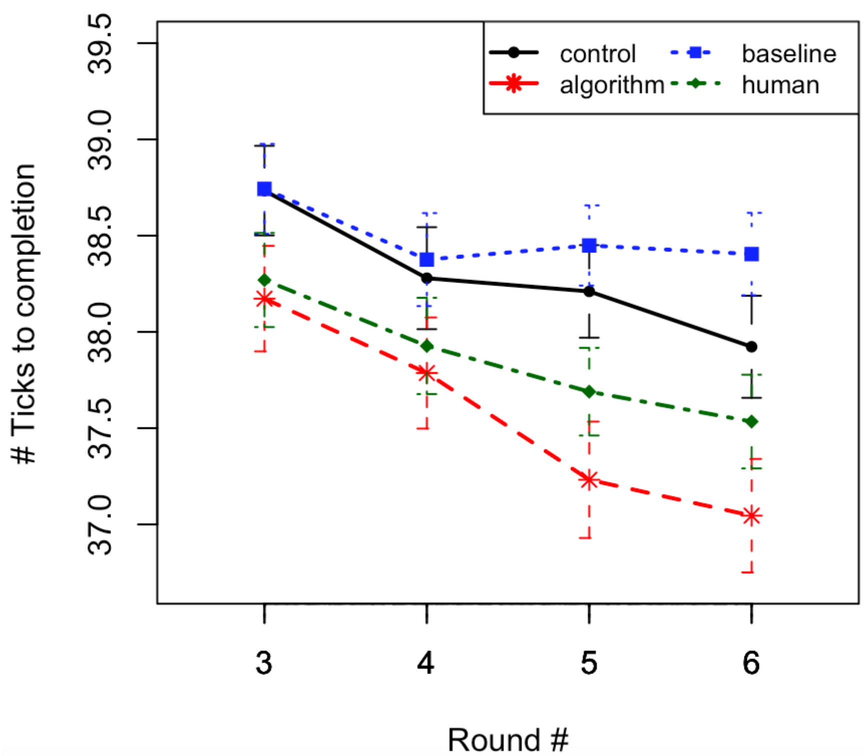
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Results Our Tip Improves Performance

Ticks to completion



One-sided T-Tests

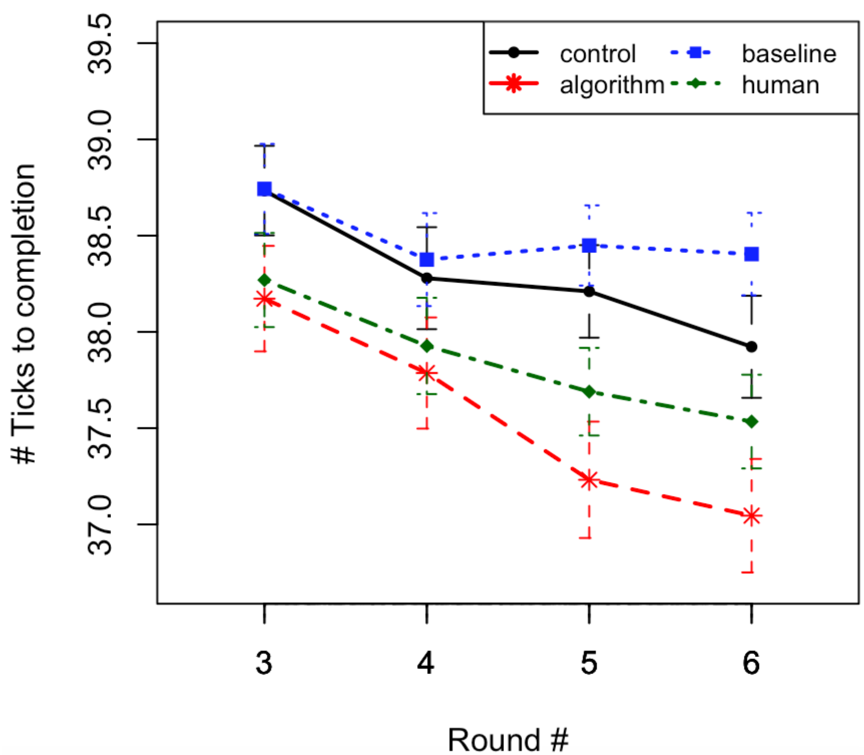
Algorithm *beats* Control ($p = 0.000008$)
Algorithm *beats* Human ($p = 0.006$)
Algorithm *beats* Baseline ($p < 1e\text{-}12$)

Amazon Mechanical Turk, $N = 1{,}011$
mean age 34.9, 60% female

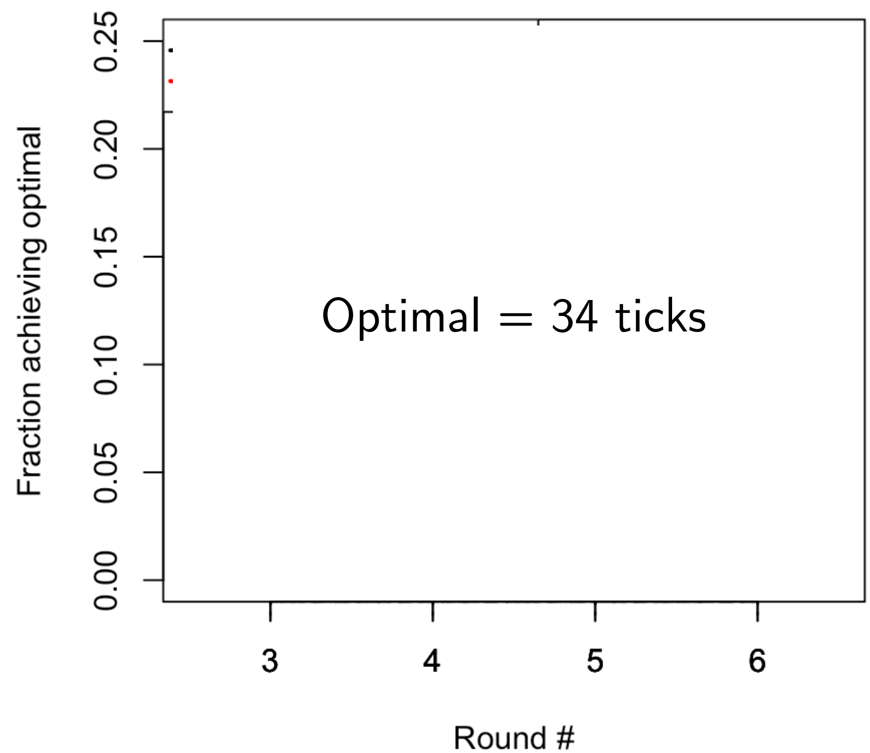
Study 1:

Results

Ticks to completion



Fraction achieving optimal



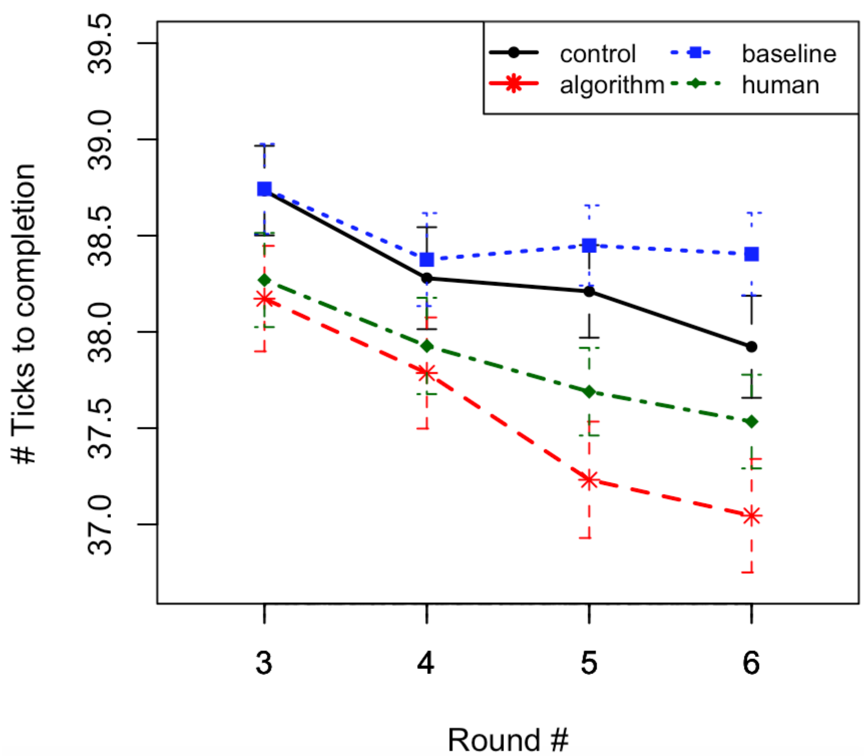
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

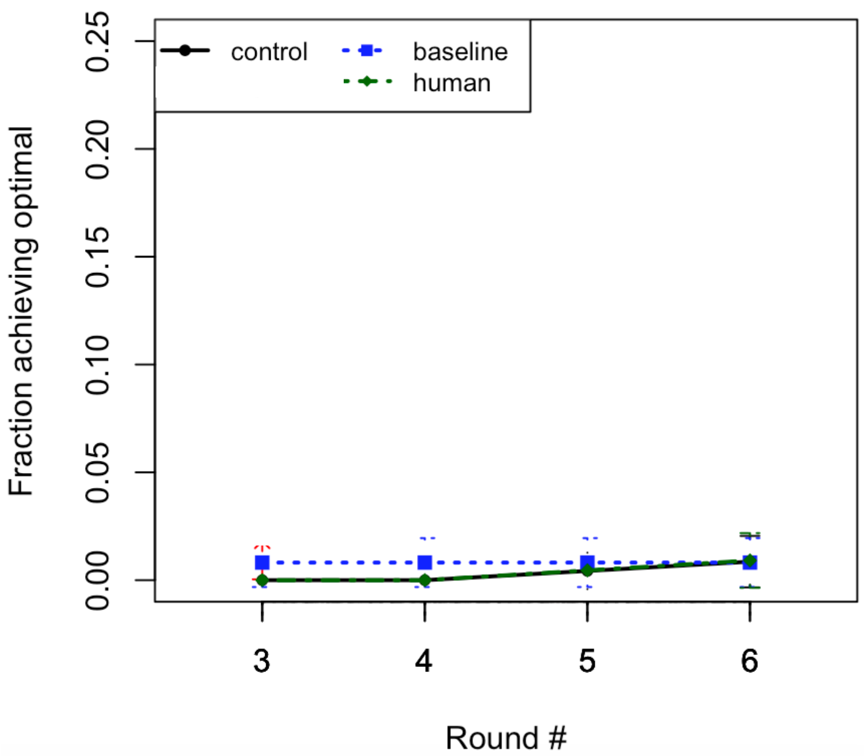
Study 1:

Results Difficult to Reach Optimal

Ticks to completion



Fraction achieving optimal



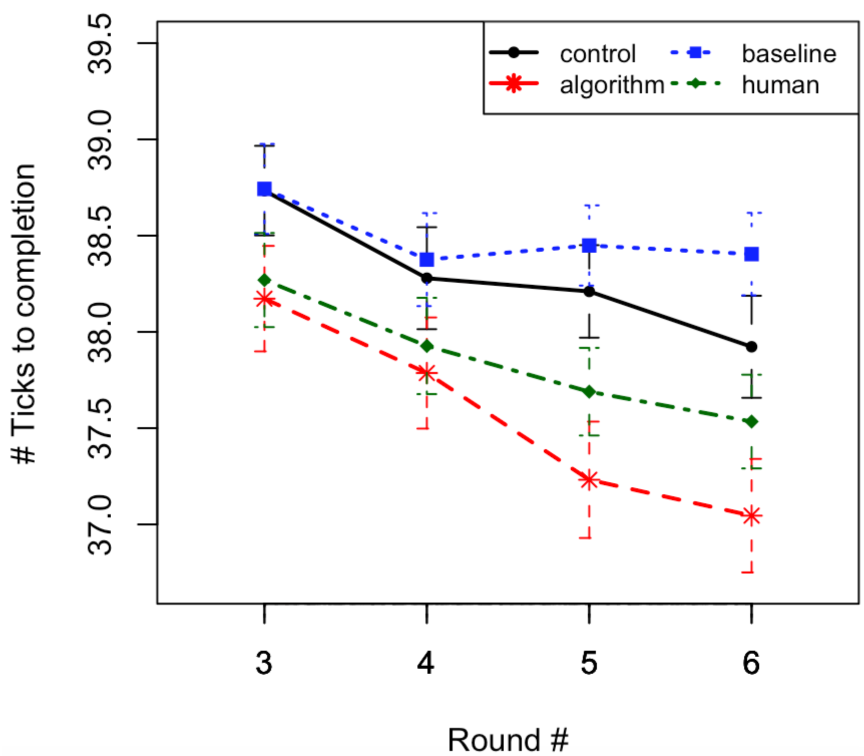
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

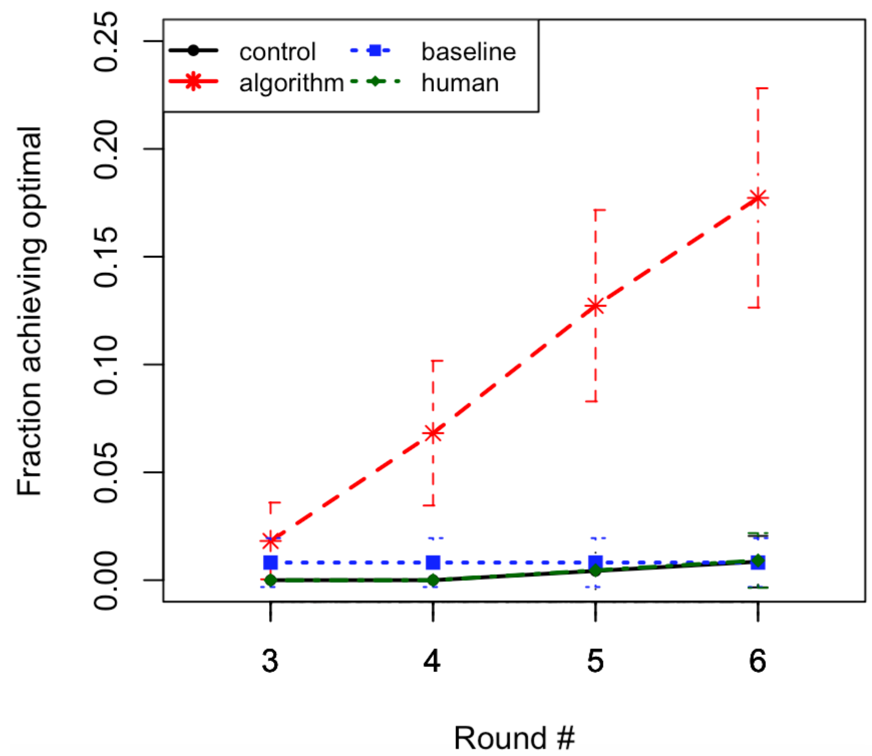
Study 1:

Results Our Tip Helps Reach Optimal

Ticks to completion



Fraction achieving optimal



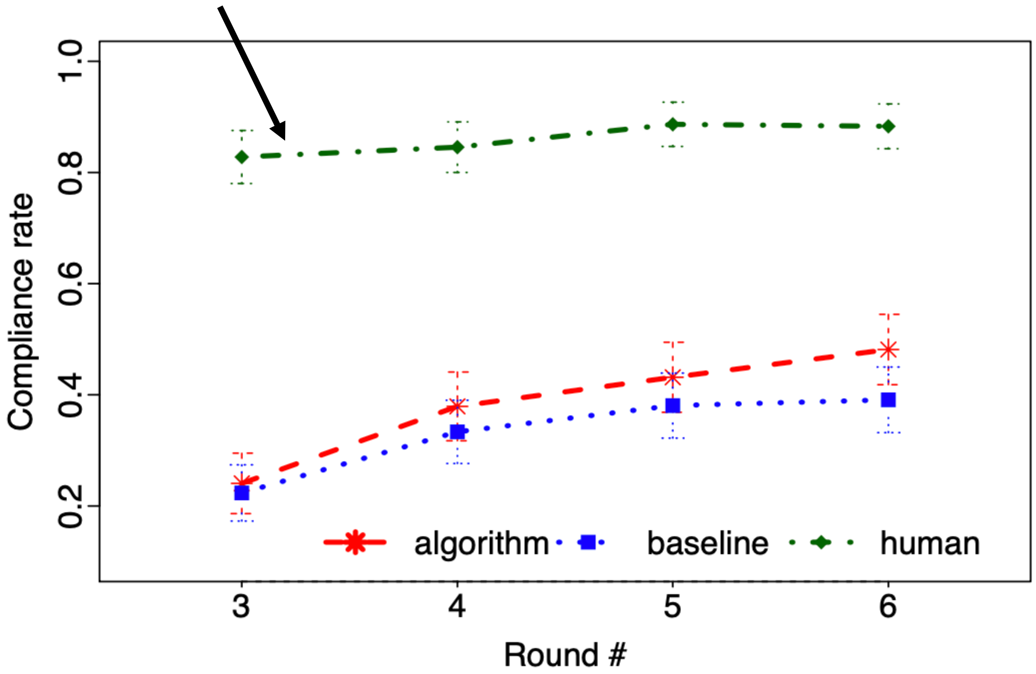
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Results Complying with Intuitive Tip

Human "Server cooks once"



Amazon Mechanical Turk, N = 1,011

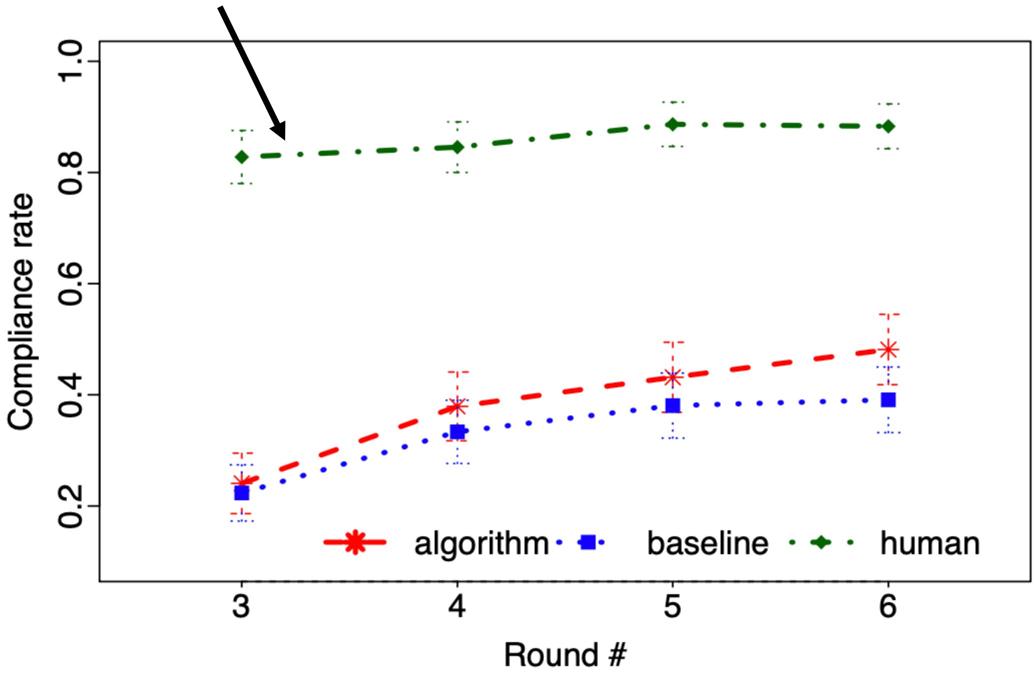
mean age 34.9, 60% female

Study 1:

Results Complying with Intuitive Tip

26% Positive, 17% Negative

Human "Server cooks once"



"I felt that tip was **valid**."

R_1rvkYTwgAjD0z4z

"It helped because she could cook one burger but **any more than that and your ticks would be too high**."

R_d6YSuigdikyaNdT

"It was **accurate**, and I implemented it."

R_1pA8wDYgWc9hblt

Amazon Mechanical Turk, N = 1,011

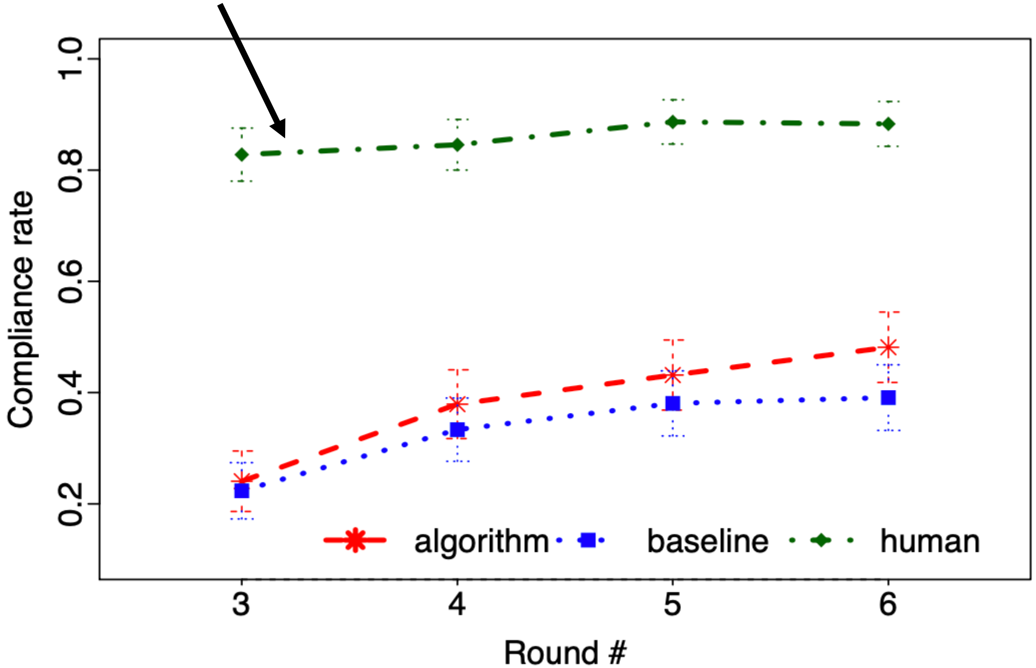
mean age 34.9, 60% female

Study 1:

Results Complying with Intuitive Tip

26% Positive, 17% Negative

Human "Server cooks once"



Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

"I felt that tip was **valid**."

R_1rvkYTwgAjD0z4z

"It helped because she could cook one burger but **any more than that and your ticks would be too high**."

R_d6YSuigdikyaNdT

"It was **accurate**, and I implemented it."

R_1pA8wDYgWc9hblt

"It stunk honestly. **The server takes forever to cook."**

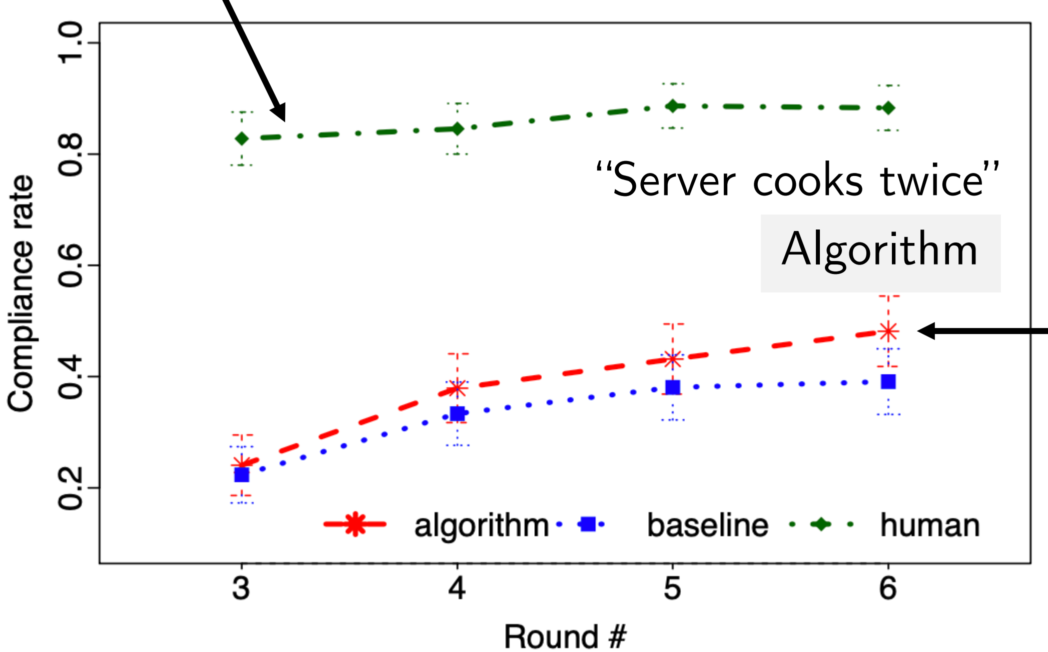
R_beijQ8guDyExa5r

"I used the tip but **I don't think it was helpful.** The server took long to cook."

Study 1:

Results Against Counterintuitive Tips

Human "Server cooks once"



"Server cooks twice"

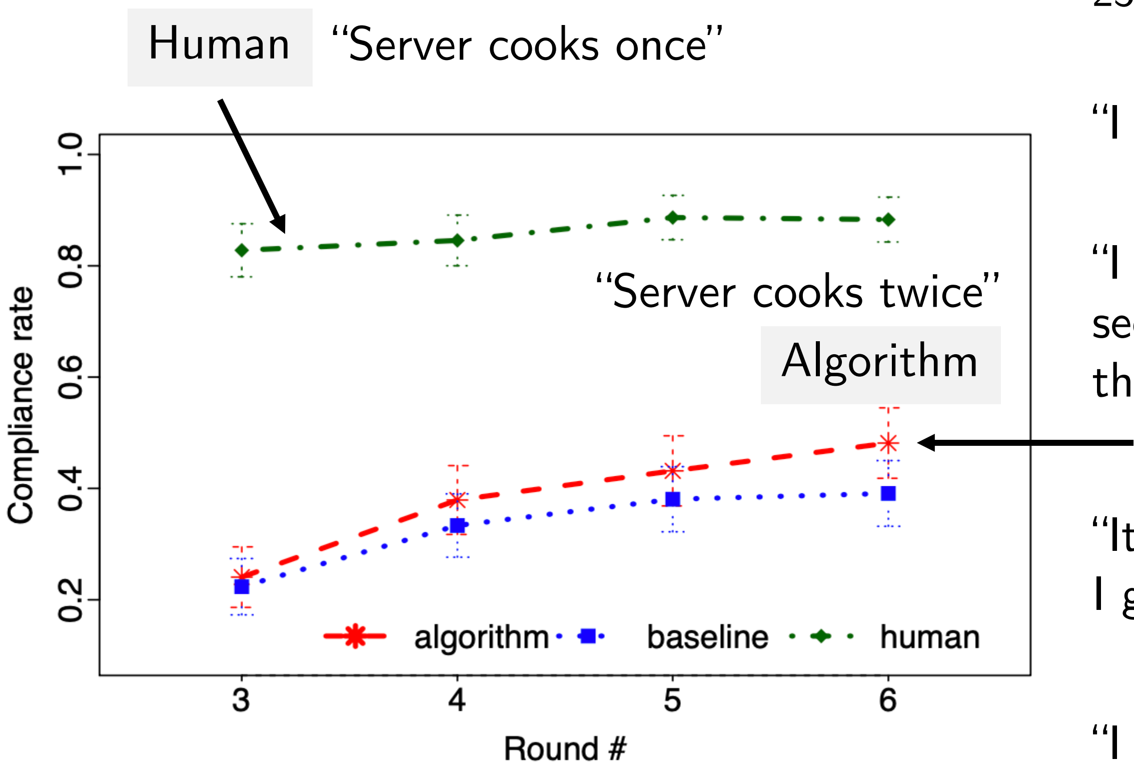
Algorithm

Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Results Against Counterintuitive Tips



23% Positive, **33% Negative**

"I didn't think it was right."

R_3EgrcrQouPcb1fS

"I didn't follow it because it seemed counter intuitive since they're slow."

R_10HkPUkR6o0qDFT

"It didn't make sense and in fact I got worse trying to use it,"

R_2YD5x6BL7mhCYEP

"I wasn't sure how to use it."

R_2s0UA1omAifrFgx

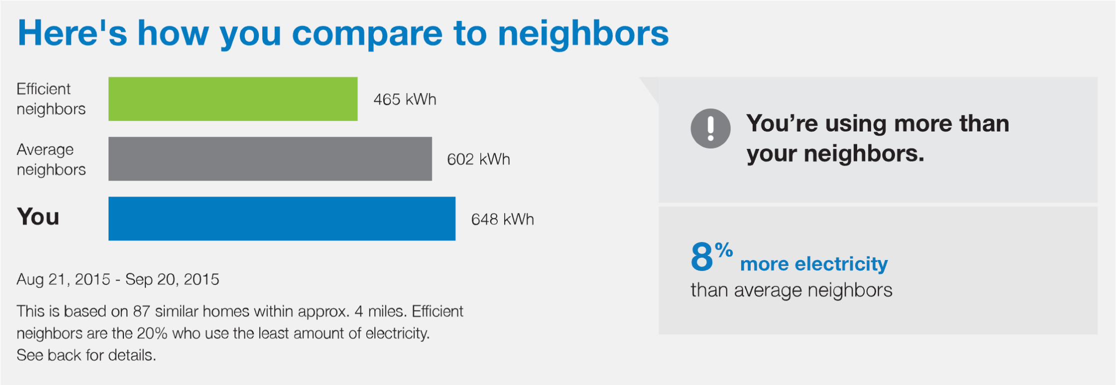
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Improving Compliance?

Improving Compliance

Social information



Allcott 2011, *Journal of Public Economics*

Improving Compliance

Social information

> "The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks."

in all 4 disrupted rounds (3-6)

Improving Compliance

Social information

> "The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks."

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"Pay" – incentive to try

Improving Compliance

Social information

> "The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks."

in all 4 disrupted rounds (3-6)

"Pay" – incentive to try

> "You'll earn the maximum bonus if server cooks twice in this round."

in rounds 3-4, back to original scheme in rounds 5-6

Improving Compliance

Social information

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"Curriculum" – pacing learning

Improving Compliance

Social information

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"You'll earn the maximum bonus if server cooks twice in this round."

in rounds 3-4, back to original scheme in rounds 5-6

"Curriculum" – pacing learning

Algorithm	Human	Hypothetical
Server should cook twice	Server should cook once	Server shouldn't cook

Improving Compliance

Social information

"The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks."

in all 4 disrupted rounds (3-6)

"Pay" – incentive to try

"You'll earn the maximum bonus if server cooks twice in this round."

in rounds 3-4, back to original scheme in rounds 5-6

"Curriculum" – pacing learning

Algorithm	Human	Hypothetical
Server should cook twice	Server should cook once ←	Server shouldn't cook

in round 3

Improving Compliance

Social information

“The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks.”

in all 4 disrupted rounds (3-6)

“Pay” – incentive to try

“You’ll earn the maximum bonus if server cooks twice in this round.”

in rounds 3-4, back to original scheme in rounds 5-6

“Curriculum” – pacing learning

Algorithm	Human	Hypothetical
Server should cook twice	Server should cook once	Server shouldn’t cook
in rounds 4-6	in round 3	

Improving Compliance

Social information

> "The majority of best players adopted this rule [Server Cook Twice], enabling them to achieve the optimal performance of 34 ticks."

in all 4 disrupted rounds (3-6)

"Pay + Social"

"Pay" – incentive to try

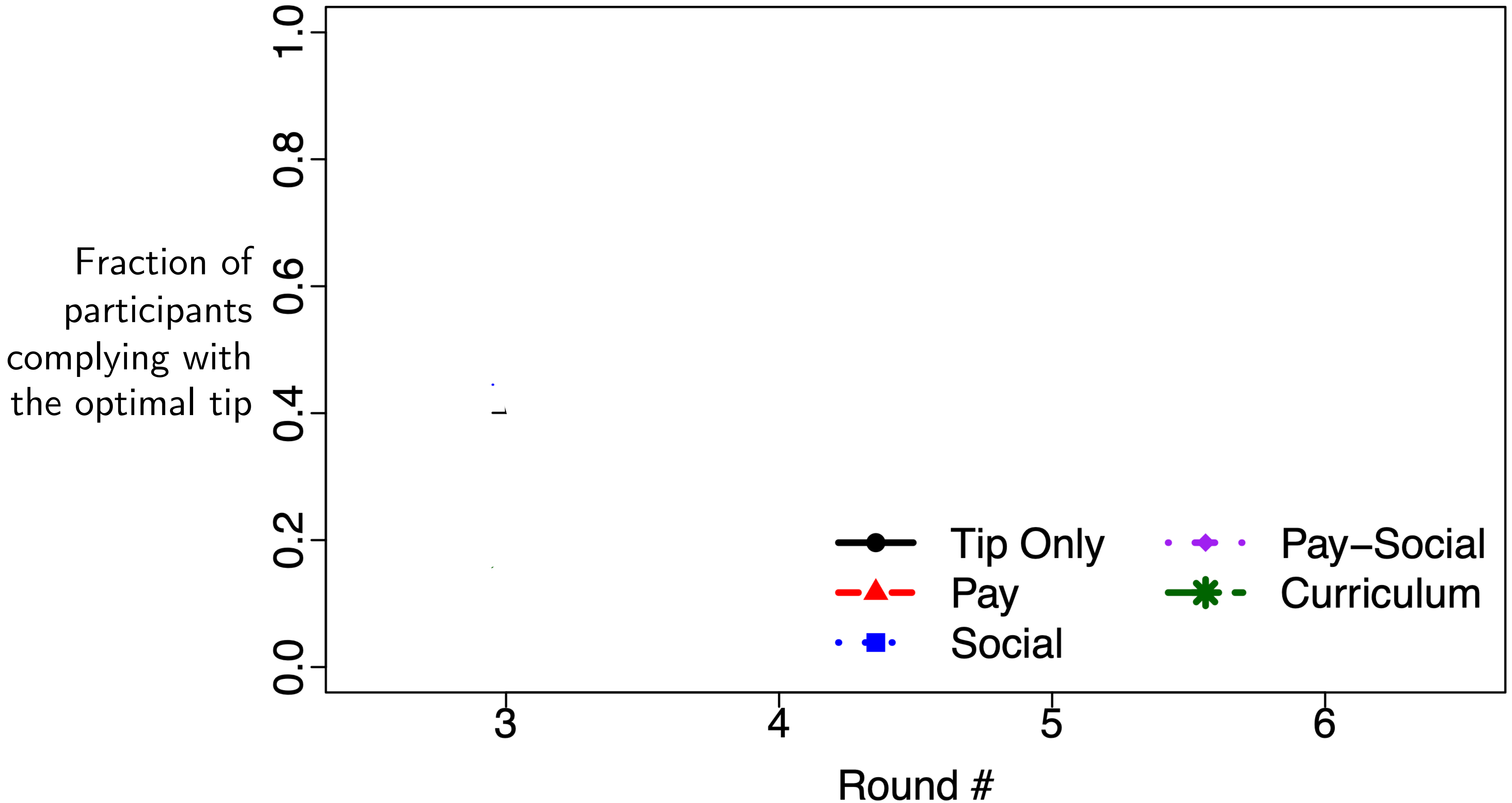
> "You'll earn the maximum bonus if server cooks twice in this round."

in rounds 3-4, back to original scheme in rounds 5-6

"Curriculum" – pacing learning

Algorithm		Human		Hypothetical
Server should cook twice	←	Server should cook once	←	Server shouldn't cook
in rounds 4-6		in round 3		

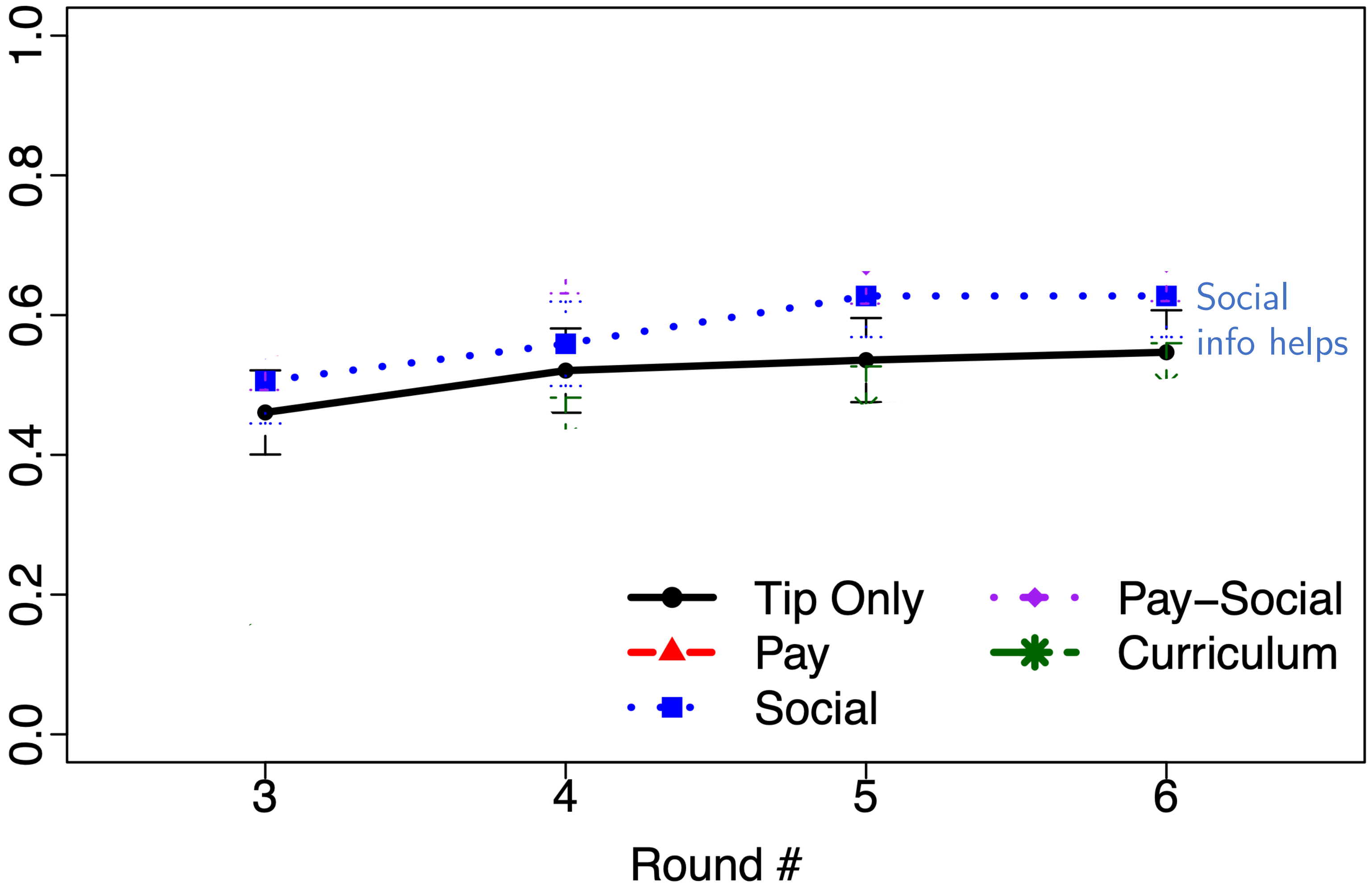
Improving Compliance



Amazon Mechanical Turk, N = 1,416

Improving Compliance

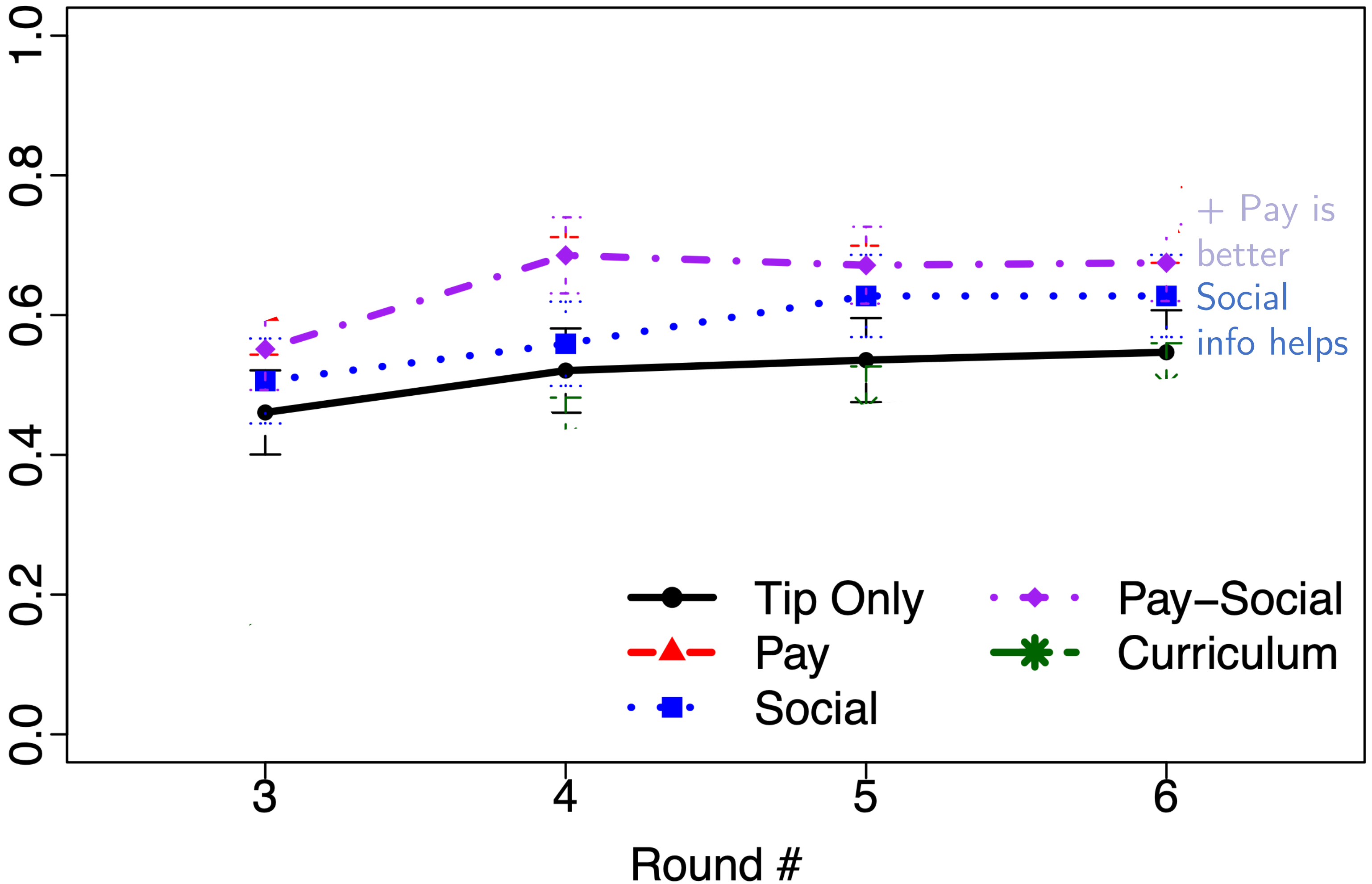
Fraction of participants complying with the optimal tip



Amazon Mechanical Turk, N = 1,416

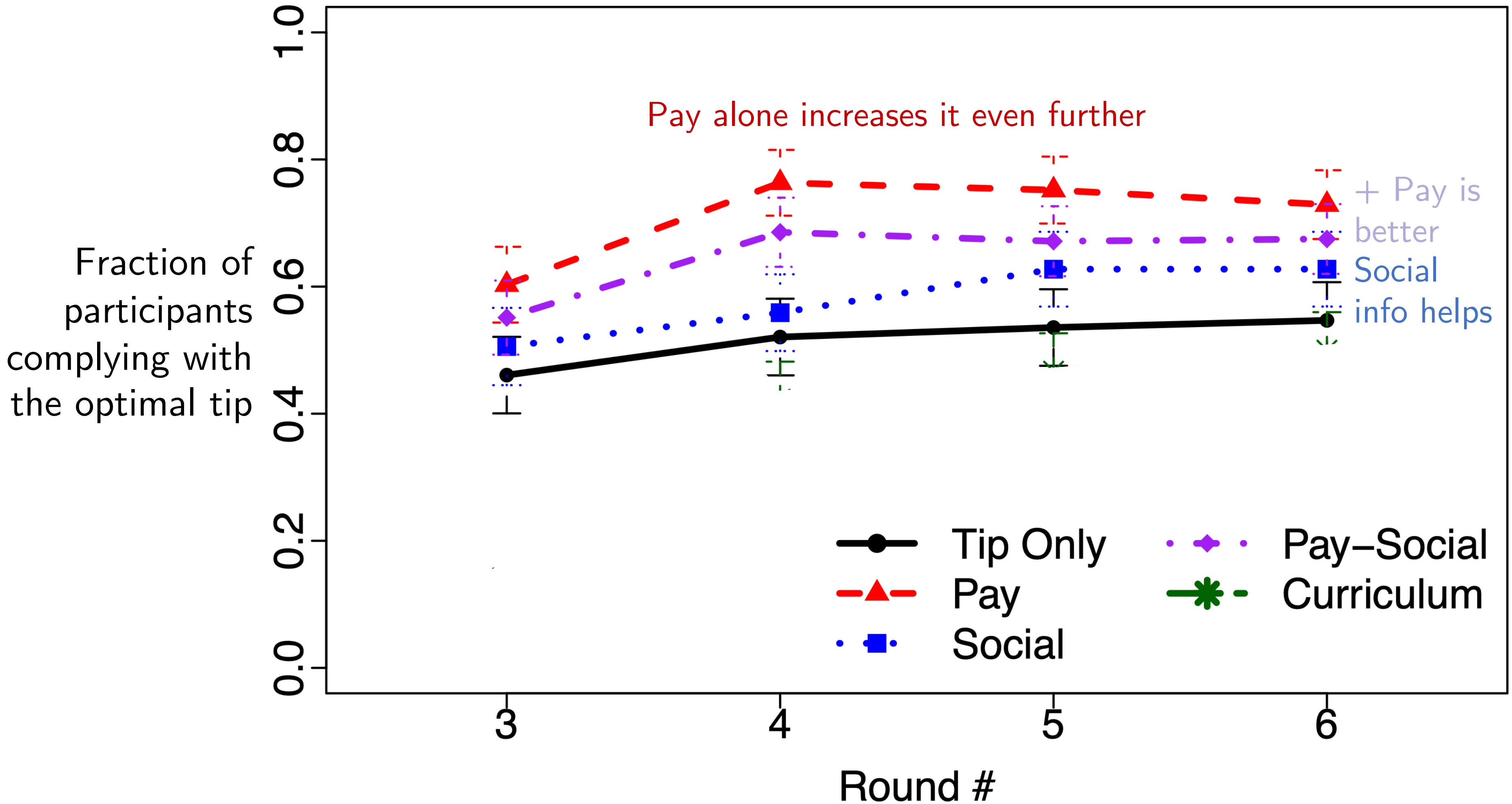
Improving Compliance

Fraction of participants complying with the optimal tip



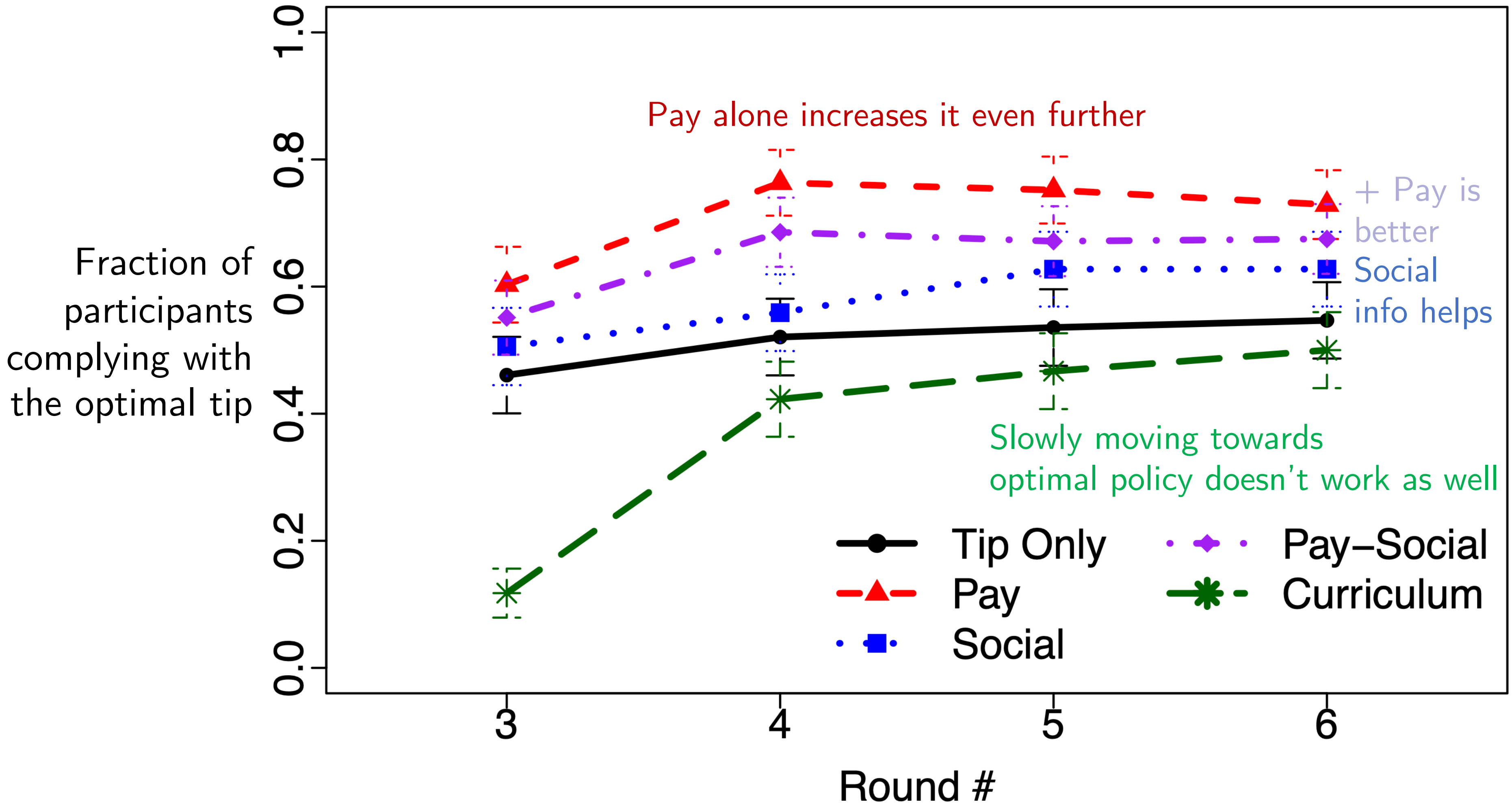
Amazon Mechanical Turk, N = 1,416

Improving Compliance



Amazon Mechanical Turk, N = 1,416

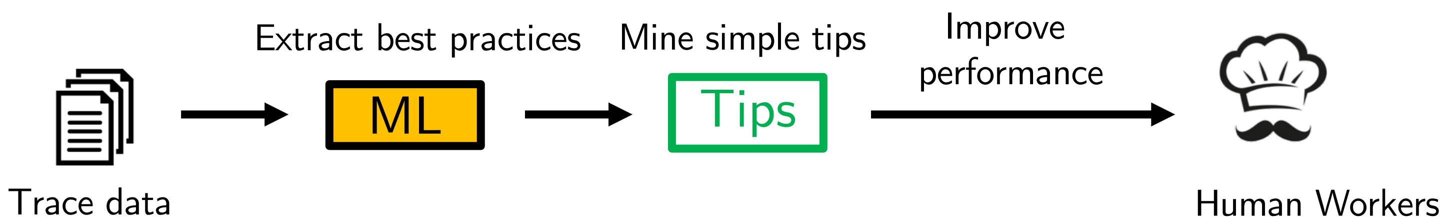
Improving Compliance



Amazon Mechanical Turk, N = 1,416

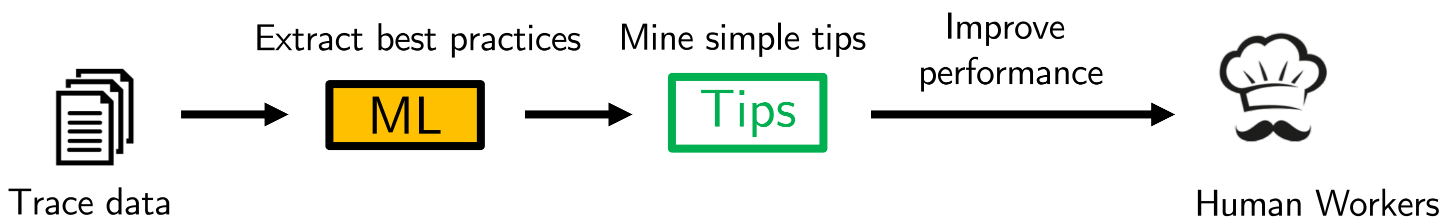
Summary

ML framework to leverage behavioral trace data to infer simple tips that help humans



Summary

ML framework to leverage behavioral trace data to infer simple tips that help humans



Our tips improve performance, speed up learning, help humans adapt to disruption, and uncover other optimal strategies

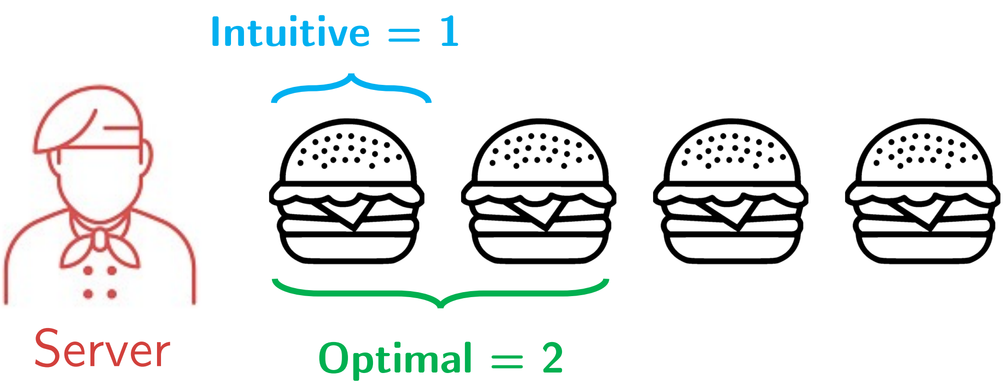
Performance/compliance tradeoff

with Hamsa Bastani & Osbert Bastani
Minor Revision @ Management Science

(Available at: bit.ly/tipspaper)

Park Sinchaisri (UC Berkeley Haas) / parksinchaisri@berkeley.edu / parksinchaisri.github.io

Study 1:



What If Decisions Are More Granular?

What If Decisions Are More Granular?

Also, What If Things Are Uncertain?

Study 2:

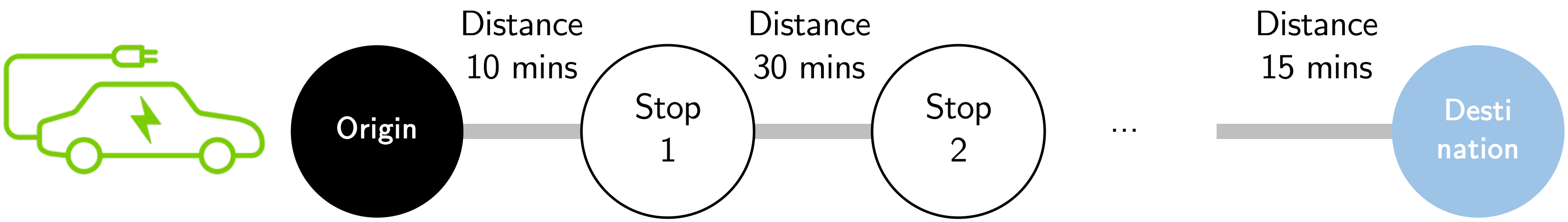
What If Decisions Are More Granular?

Also, What If Things Are Uncertain?

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

EV Charging Game



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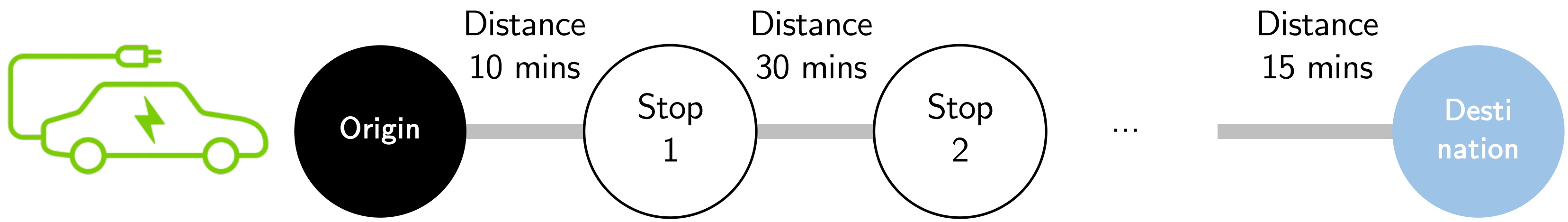
Study 2:

EV Charging Game

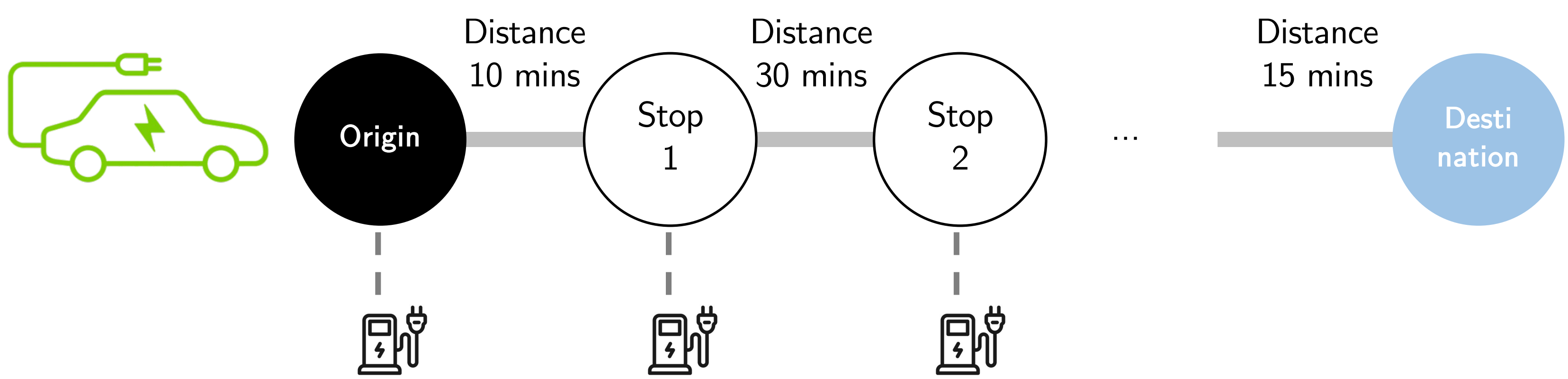


Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Study 2:

Pre-registered at https://aspredicted.org/7LP_J9G

EV Charging Game



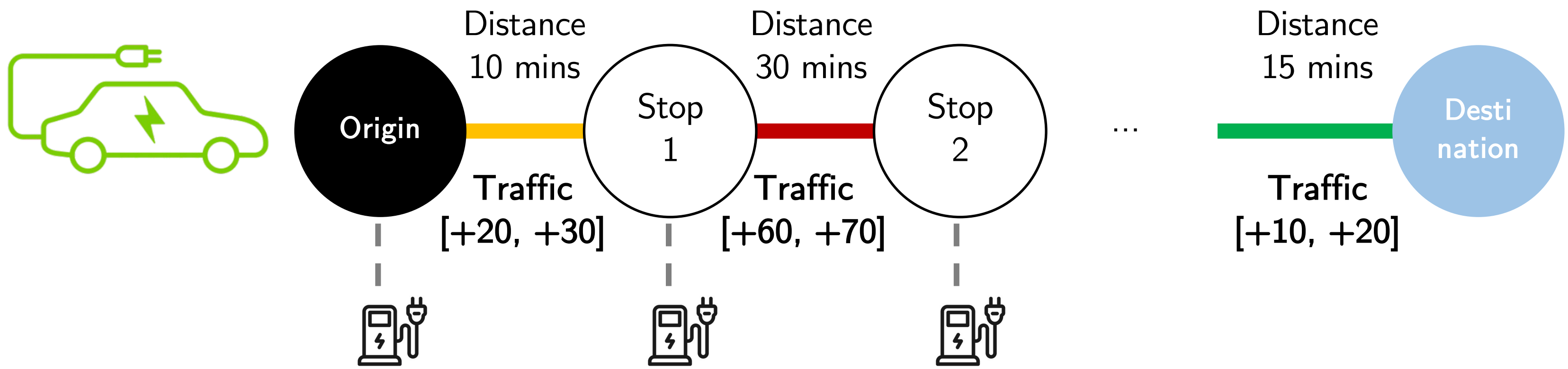
Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Challenges: Even without traffic, the amount of initial charge won't be enough

Study 2:

Pre-registered at https://aspredicted.org/7LP_J9G

EV Charging Game



Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

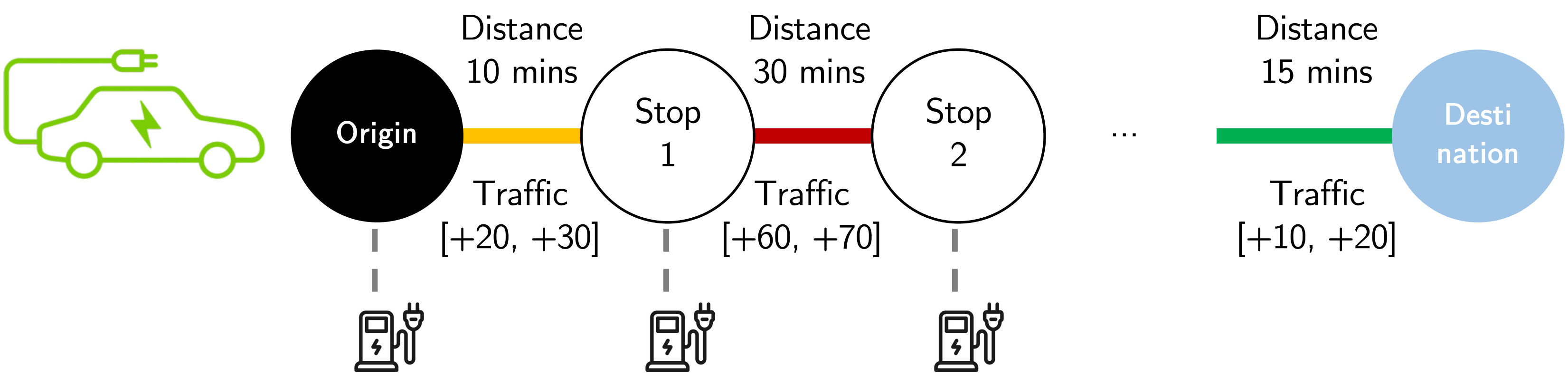
Challenges: Even without traffic, the amount of initial charge won't be enough

+ Uncertain traffic, uniformly distributed within the specified range

Study 2:

Pre-registered at https://aspredicted.org/7LP_J9G

EV Charging Game



Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

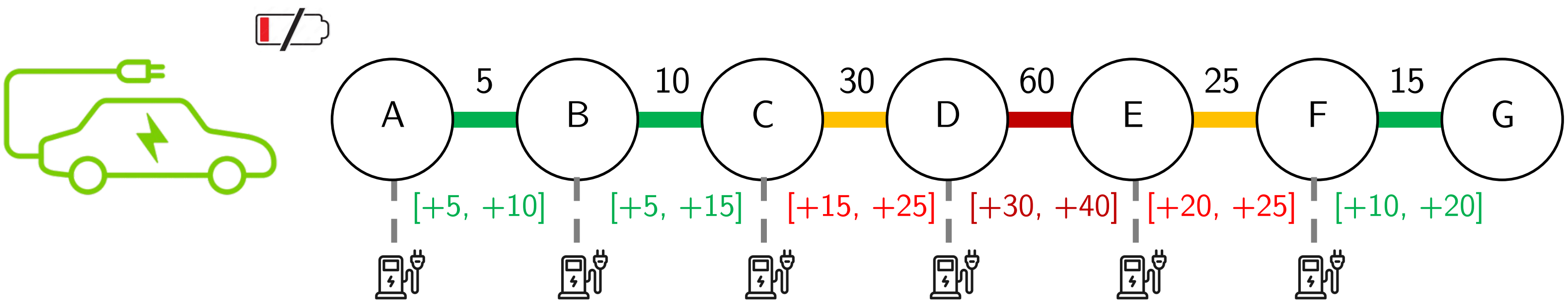
Challenges: Even without traffic, the amount of initial charge won't be enough

+ Uncertain traffic, uniformly distributed within the specified range
+ Cost to exit to charge **(+30 mins)** and nonlinear charging time
+ Penalty if running out of charge in the middle **(+300 mins)**

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

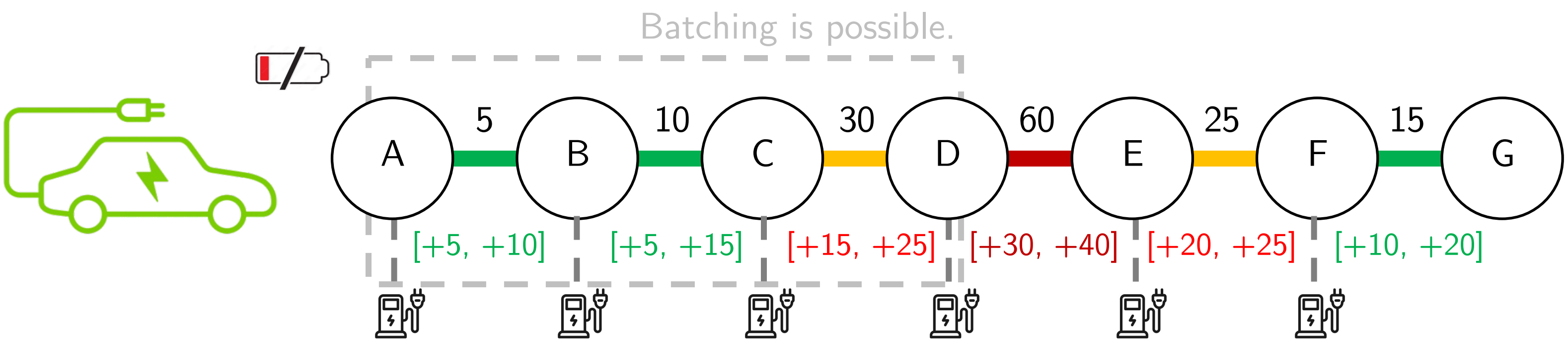
Design To Batch, or Not to Batch



Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

Design To Batch, or Not to Batch



Pre-registered at https://aspredicted.org/7LP_J9G

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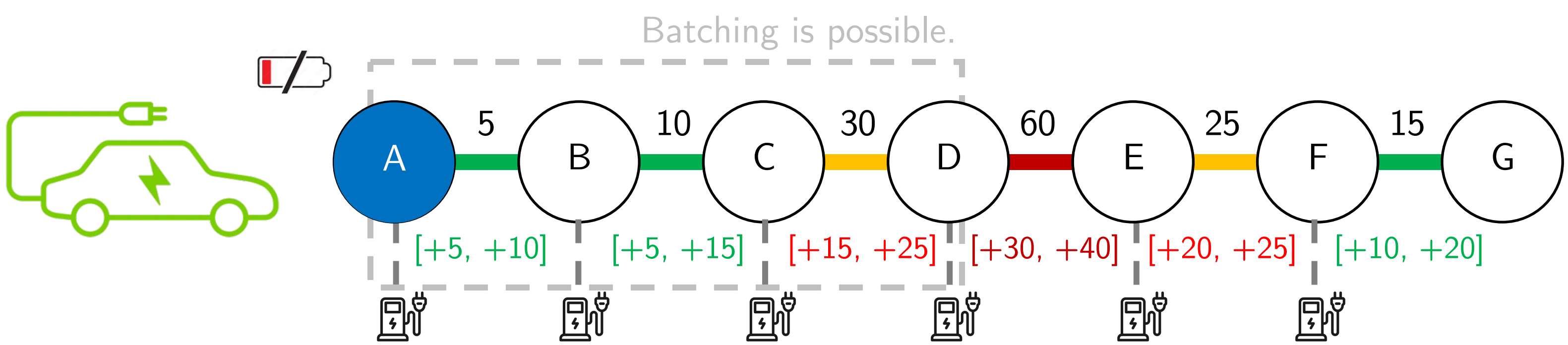


A

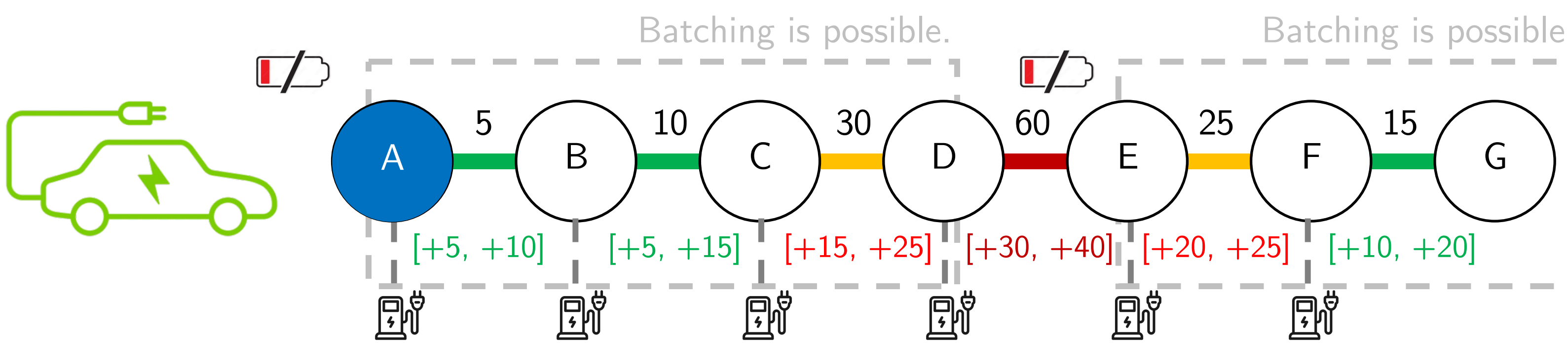
Optimal is to **"batch"** the required charges for the next two stops (A → C)

rather than just A → B or further batch A → D.

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

Design To Batch, or Not to Batch



A

Optimal is to **“batch”** the required charges for the next two stops (A → C)

rather than just A → B or further batch A → D.

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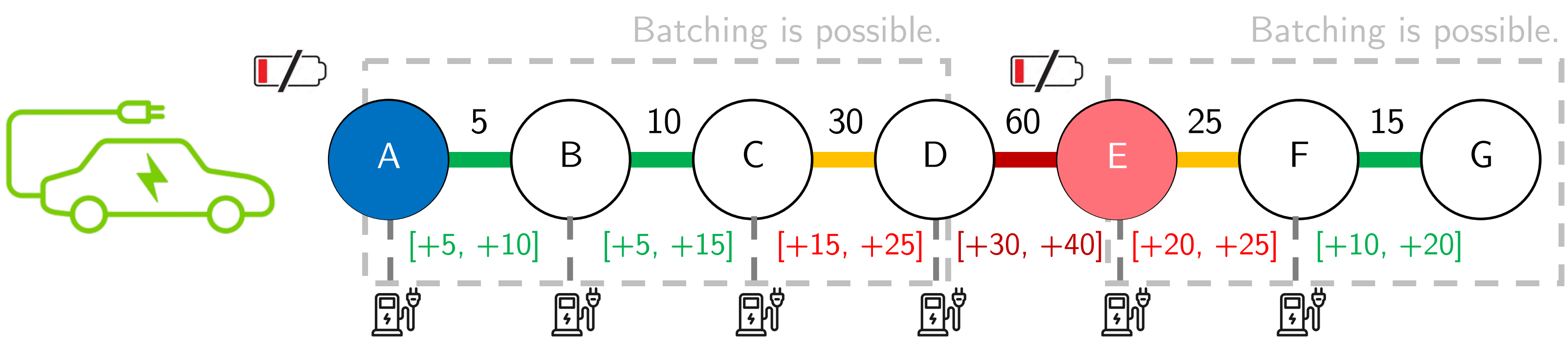
Study 2:

Design To Batch, or Not to Batch



A Optimal is to **"batch"** the required charges for the next two stops (A → C) rather than just A → B or further batch A → D.

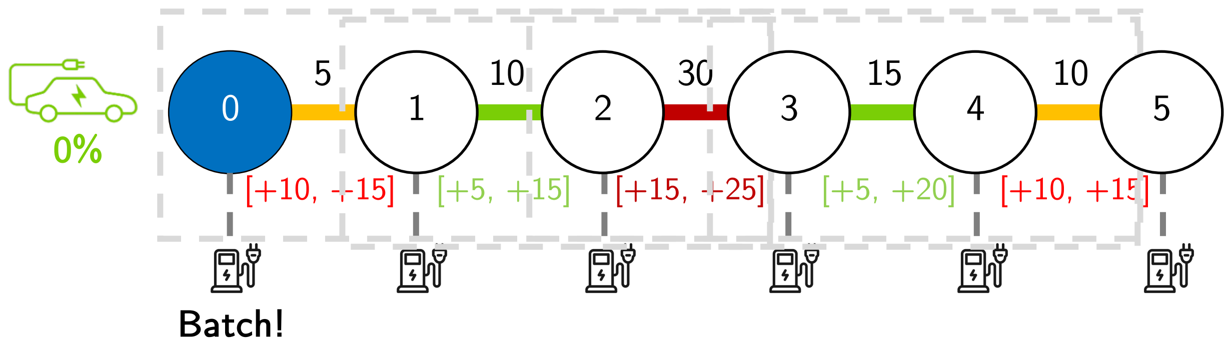
E Optimal is to **"split"** = only charge for the next stop (E → F) rather than batch E → G.

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

Design Short Map

Many batching opportunities



Short

Short (+ tip)

Short (+ tip)

Short (+ tip)

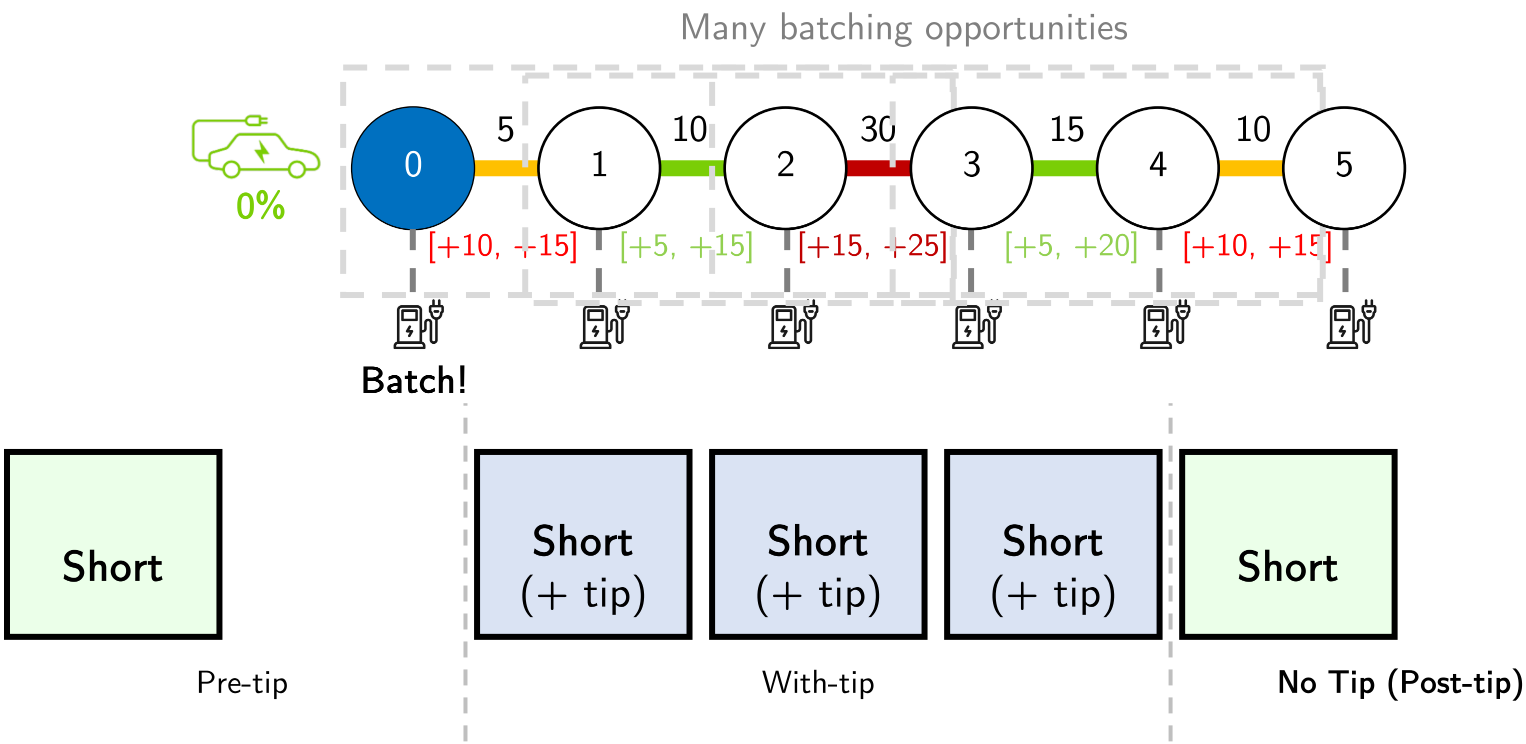
Pre-tip

With-tip

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

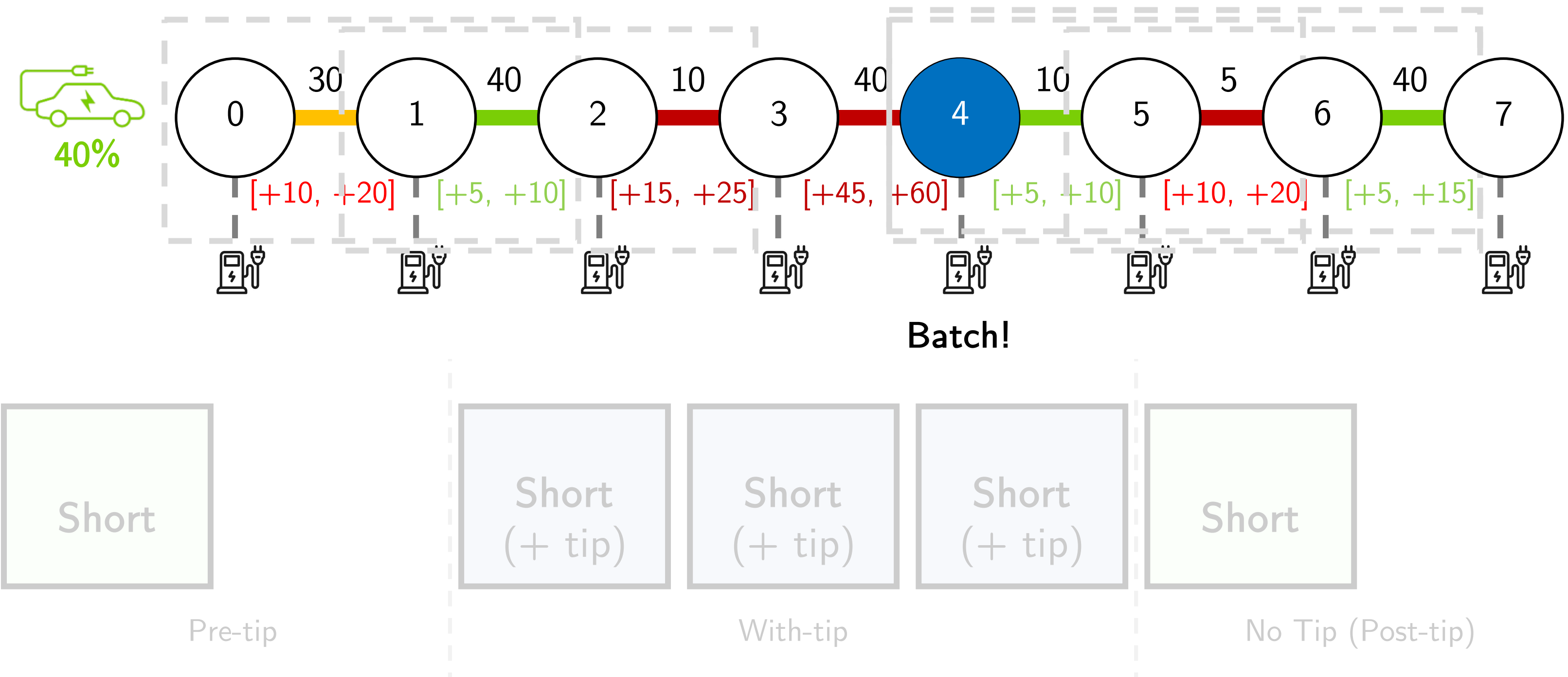
Design Short Map



Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

Design + Long Map (New Environment)



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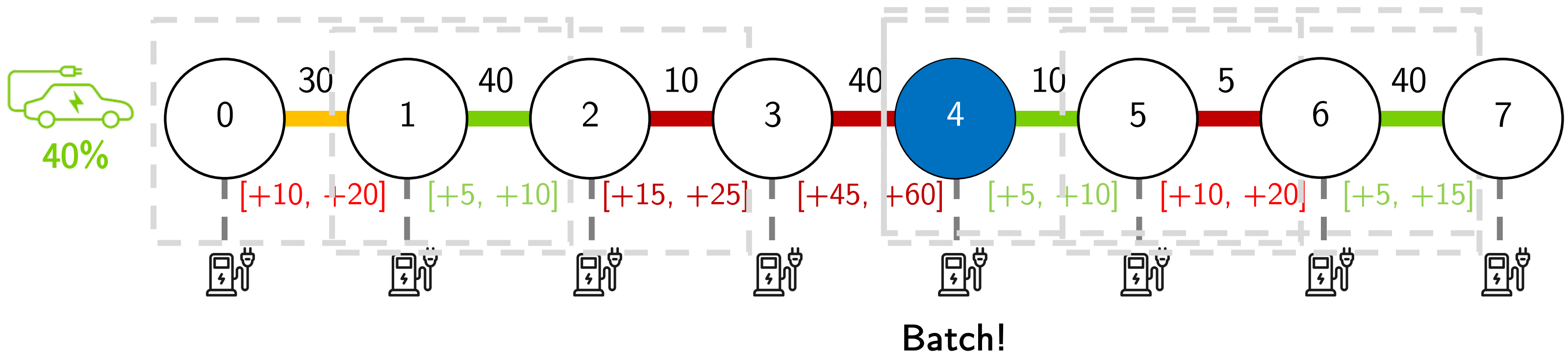
Design + Long Map (New Environment)



Round 1 **Short**	Round 2 **Long**	Round 3 **Short** (+ tip)	Round 4 **Short** (+ tip)	Round 5 **Short** (+ tip)	Round 6 **Short**	Round 7 **Long**

Pre-tip | With-tip | No Tip (Post-tip)

Pre-registered at https://aspredicted.org/7LP_J9G

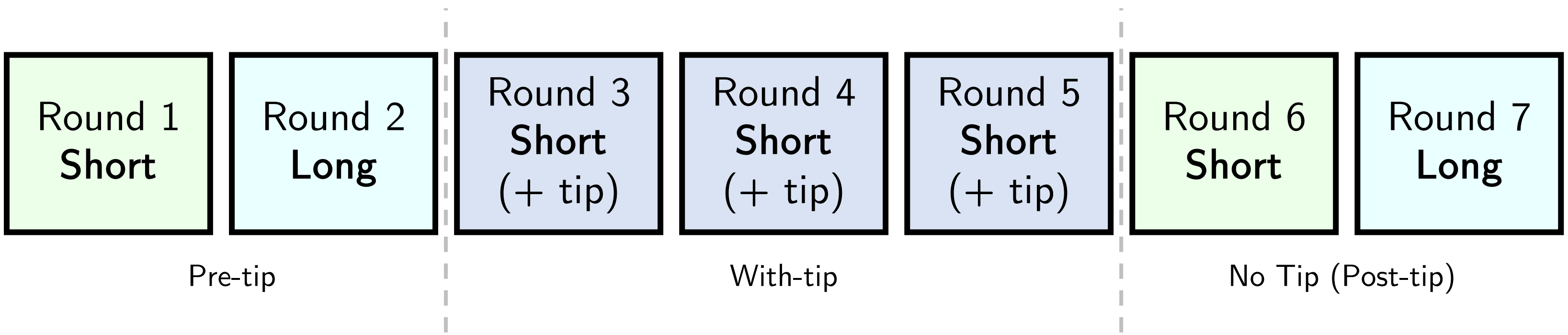
Study 2:

Design

2 x 2

tip precision

centered / skewed realized traffic



Pre-registered at https://aspredicted.org/7LP_J9G

Study 2:

Design

2 x 2

tip precision

centered / skewed realized traffic

Precise Tip:

You should exit and charge X%

Broad Tip:

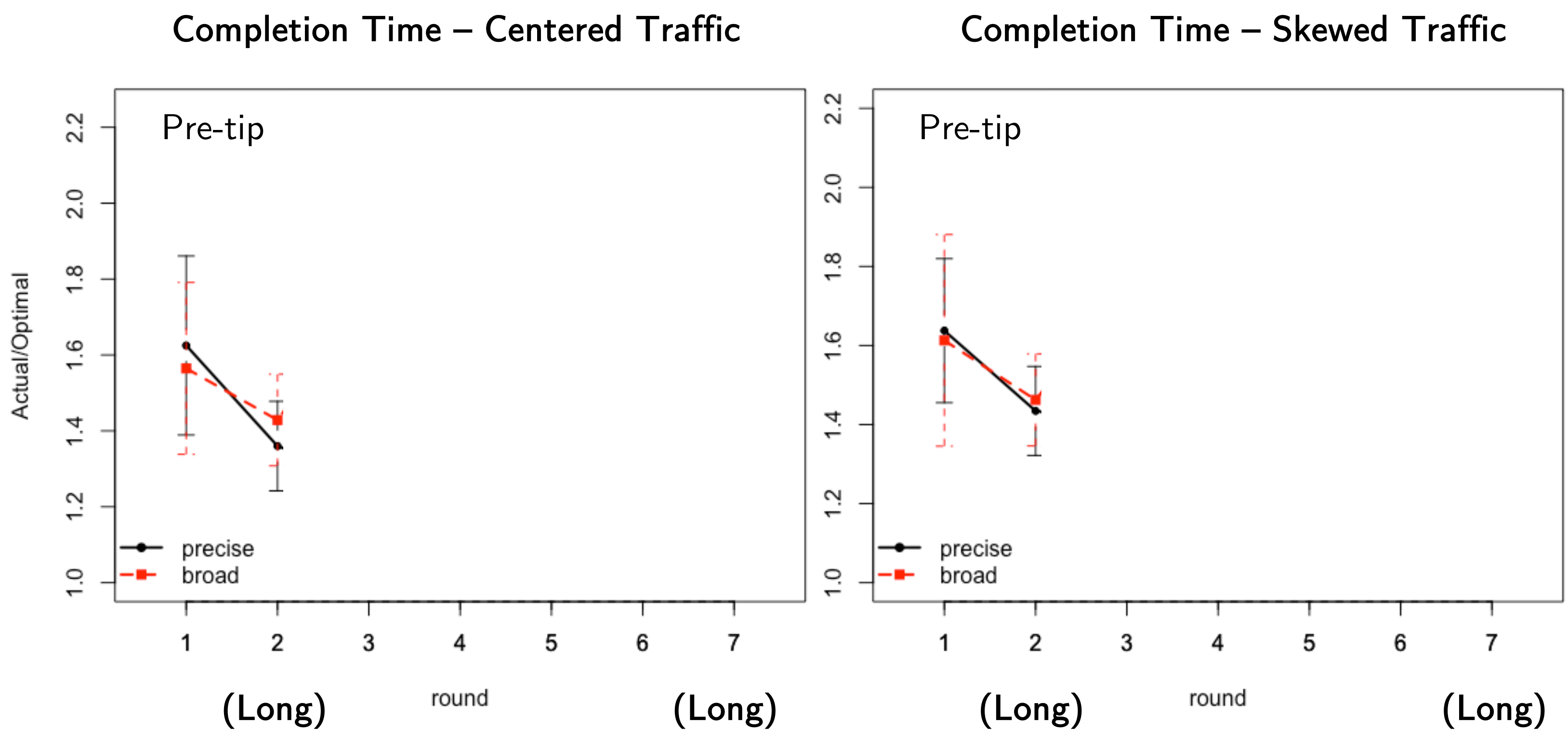
"Split" You should charge enough for this segment

"Batch" You should charge enough for this segment + next one

Round 1 **Short**	Round 2 **Long**	Round 3 **Short** (+ tip)	Round 4 **Short** (+ tip)	Round 5 **Short** (+ tip)	Round 6 **Short**	Round 7 **Long**
Pre-tip		With-tip			No Tip (Post-tip)	

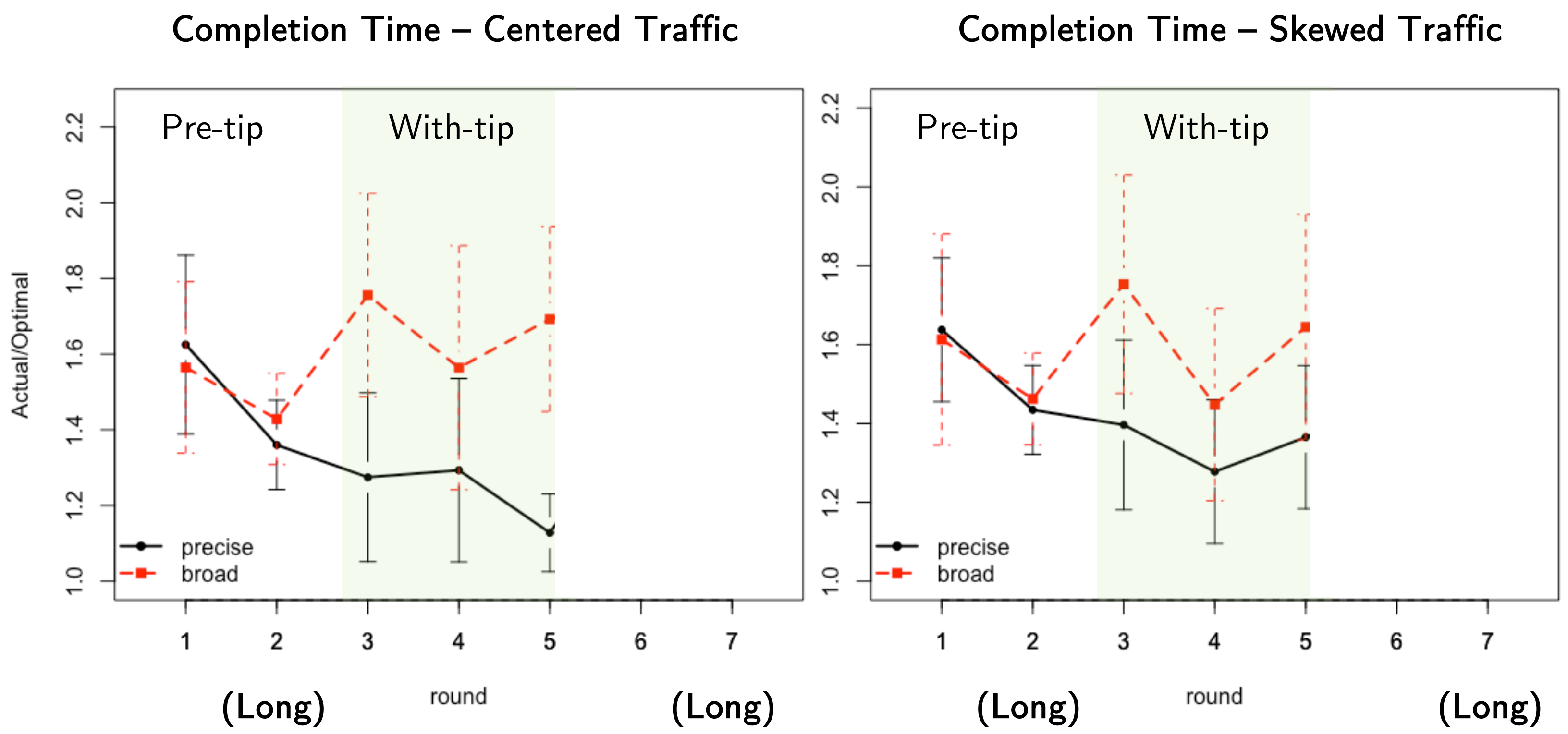
Study 2:

Results Performance Across Rounds



Amazon Mechanical Turk, N = 102, 3,978 decision points

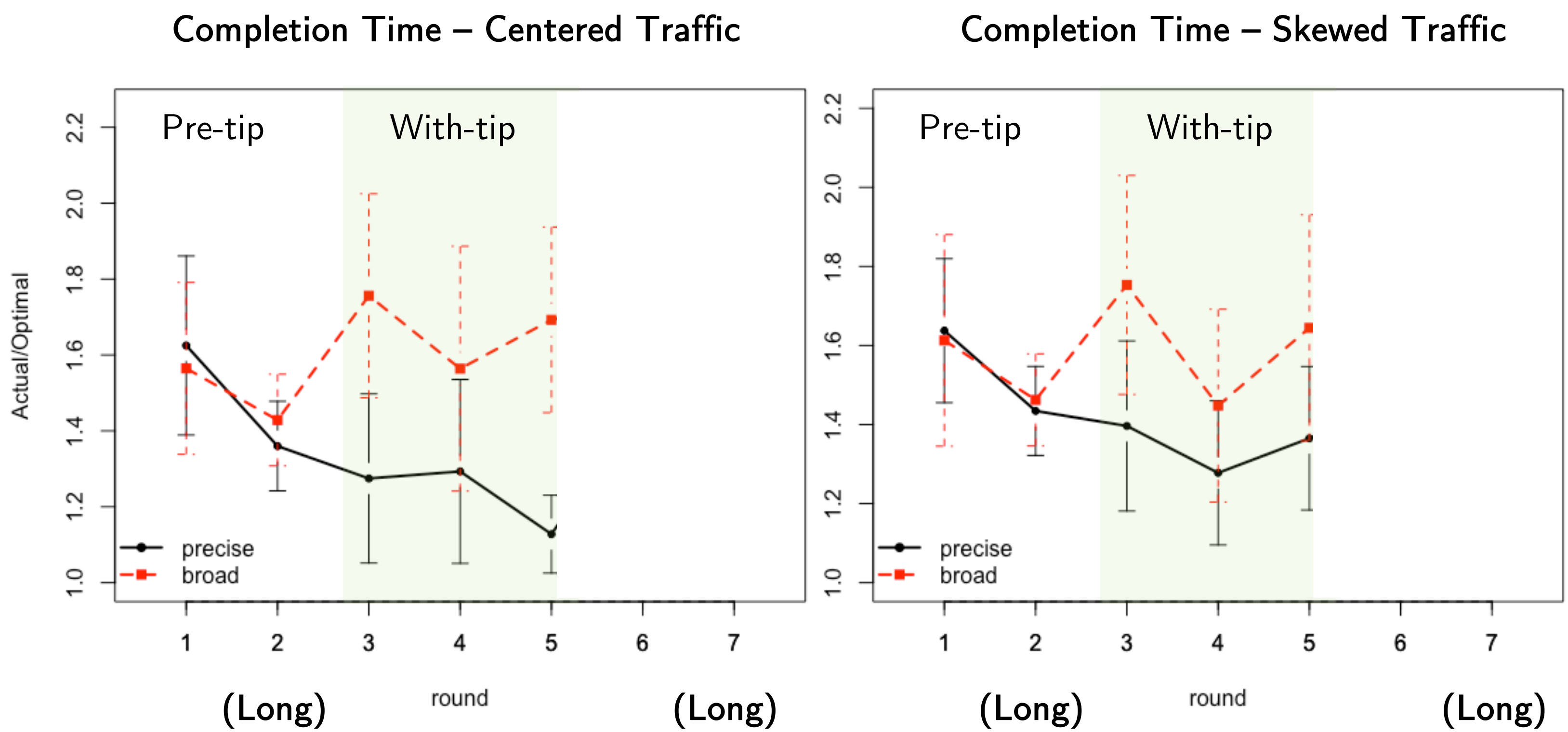
Study 2:
Results



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2:

Results Precise Tip Improves Performance



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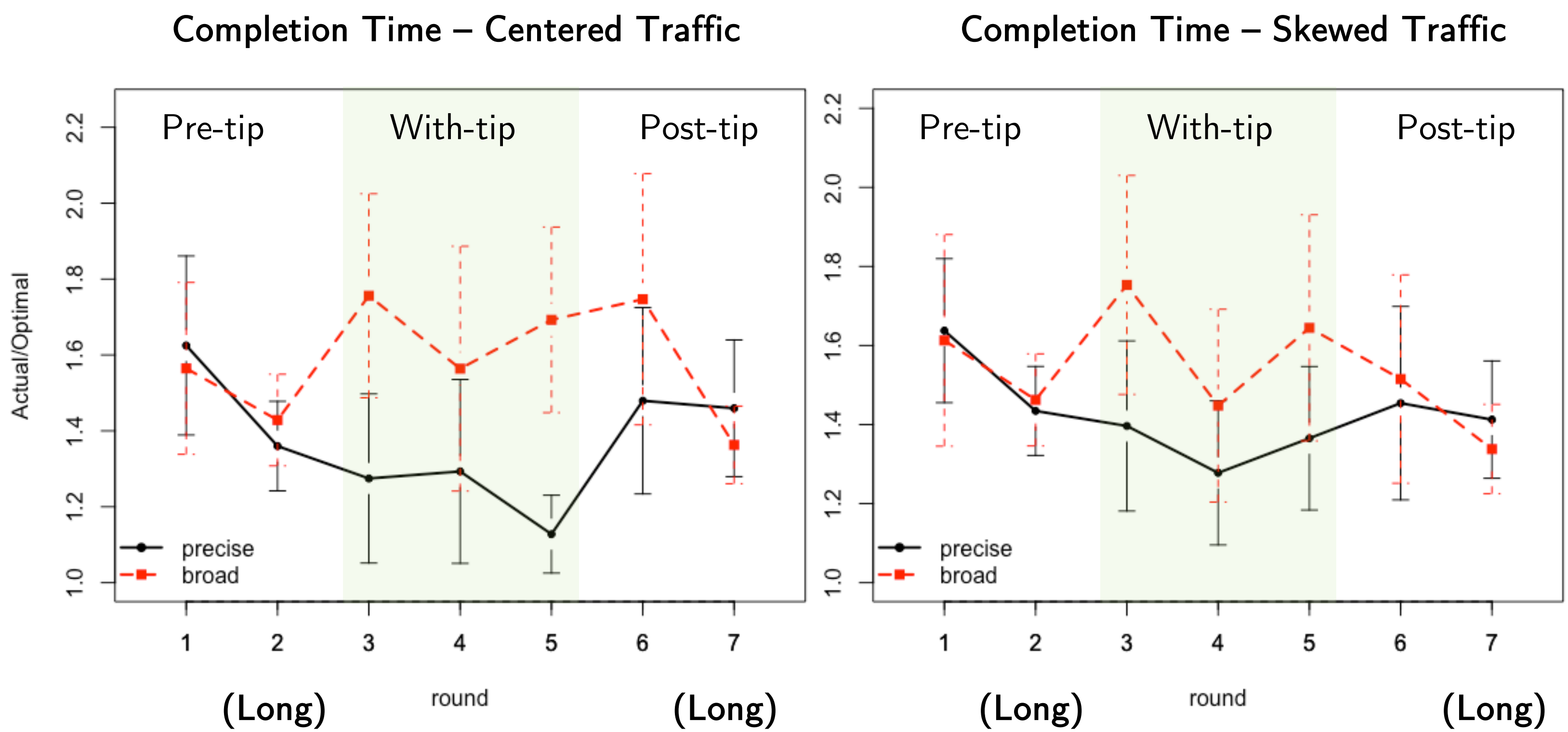
Results

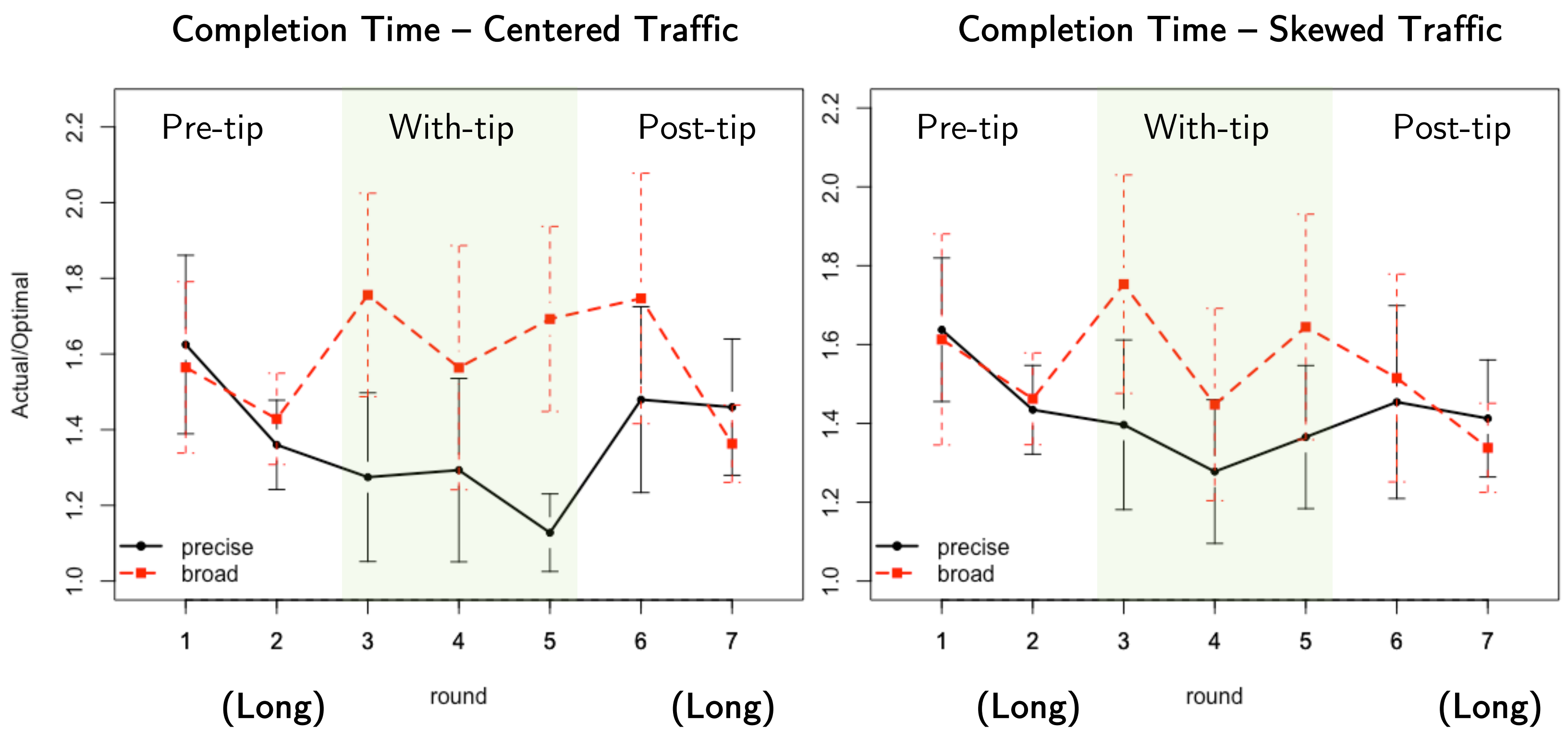


Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2:

Results

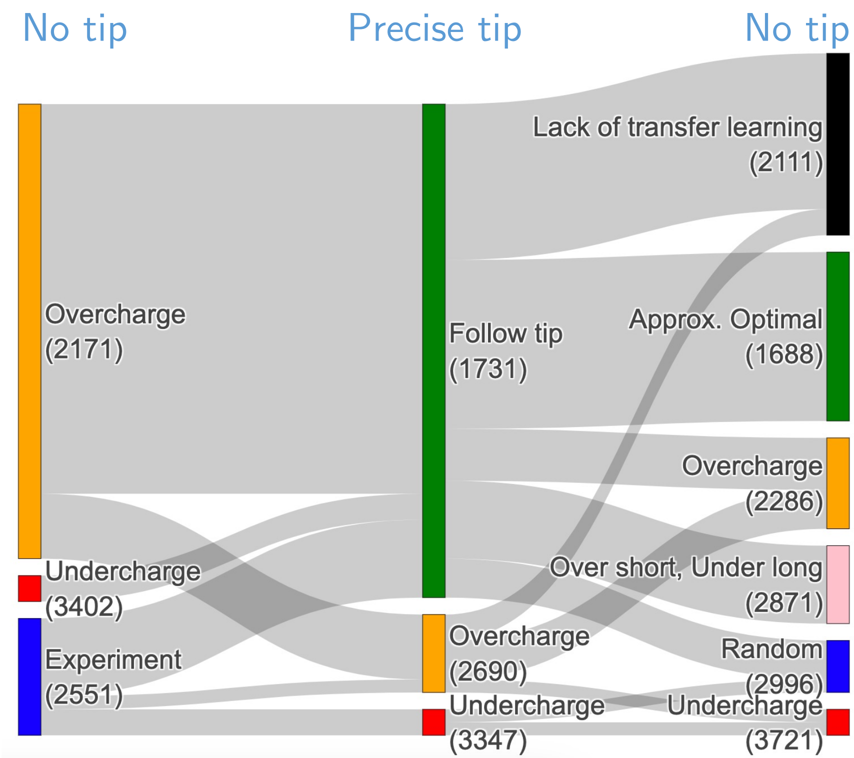
Broad Tip Seems to Help with New Environment



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2:

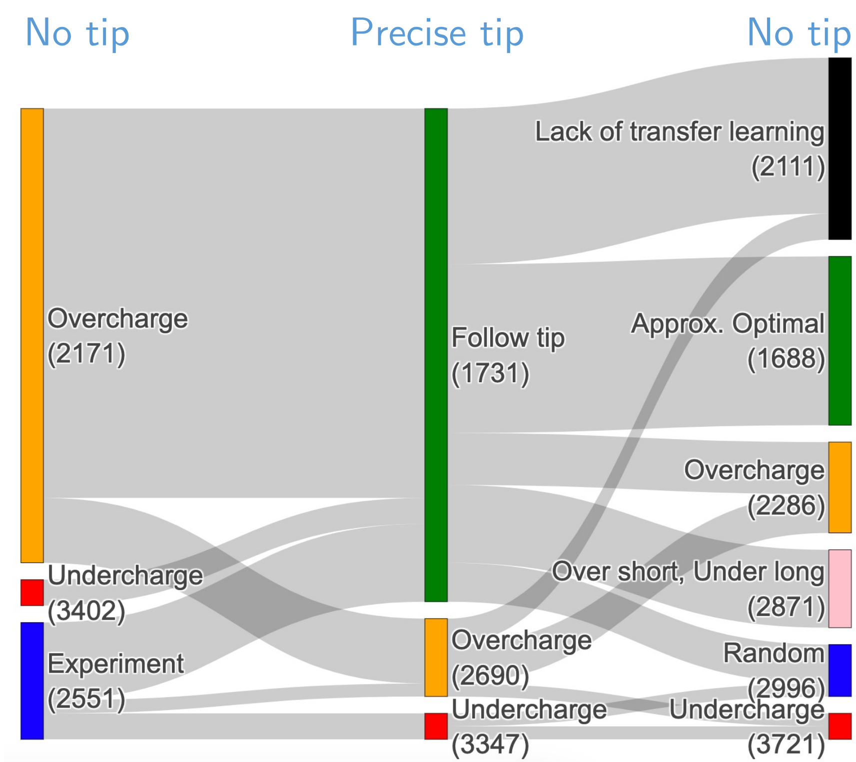
Results Long-Term Learning from Tip



34% stay with
optimal strategy afterwards

Study 2:

Results Long-Term Learning from Tip



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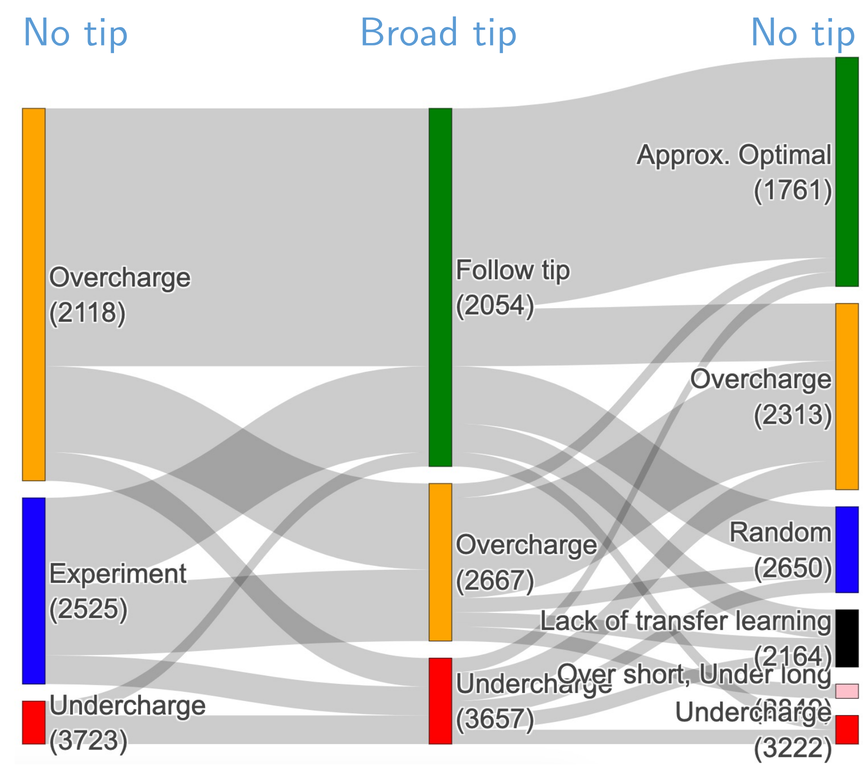
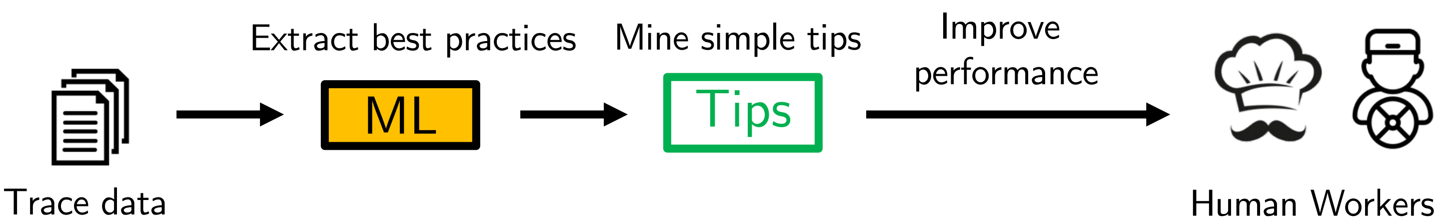


56% stay with
optimal strategy afterwards

Summary

ML framework to leverage behavioral trace data to infer simple tips that help humans



Our tips improve performance, speed up learning, help humans adapt to disruption, and uncover other optimal strategies

Performance/compliance tradeoff

with Hamsa Bastani & Osbert Bastani
Minor Revision @ Management Science

(Available at: bit.ly/tipspaper)

Pre-tip behavior classification helps predict With- and Post-tip behavior

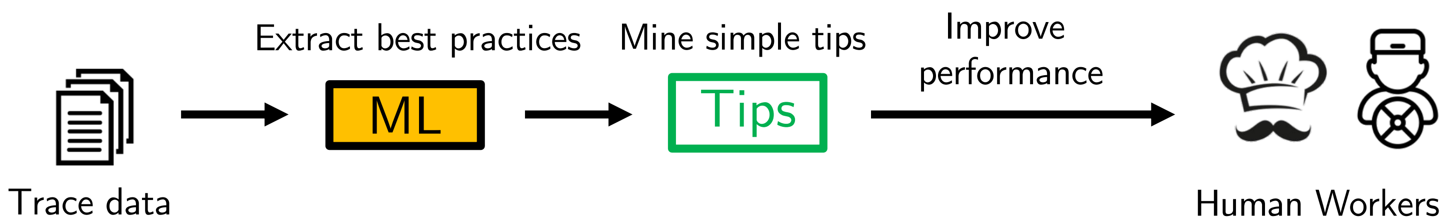
Precise tips are useful in the short term, but broad tips can help with long-term learning/new environment

with Philippe Blaettchen, *Work in Progress*

Park Sinchaisri (UC Berkeley Haas) / parksinchaisri@berkeley.edu / parksinchaisri.github.io

Summary

ML framework to leverage behavioral trace data to infer simple tips that help humans



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with Philippe Blaettchen, *Work in Progress*

Thank you! Feedback (+ tips) very welcome!

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Appendix

Study 1:

Results Learning Beyond Tips

Structure of Optimal Policy

		Chop	Cook	Plate	
Sous-Chef	2	3	2	2	times
Server	3	1	2	2	times

Algorithm Baseline

Study 1:

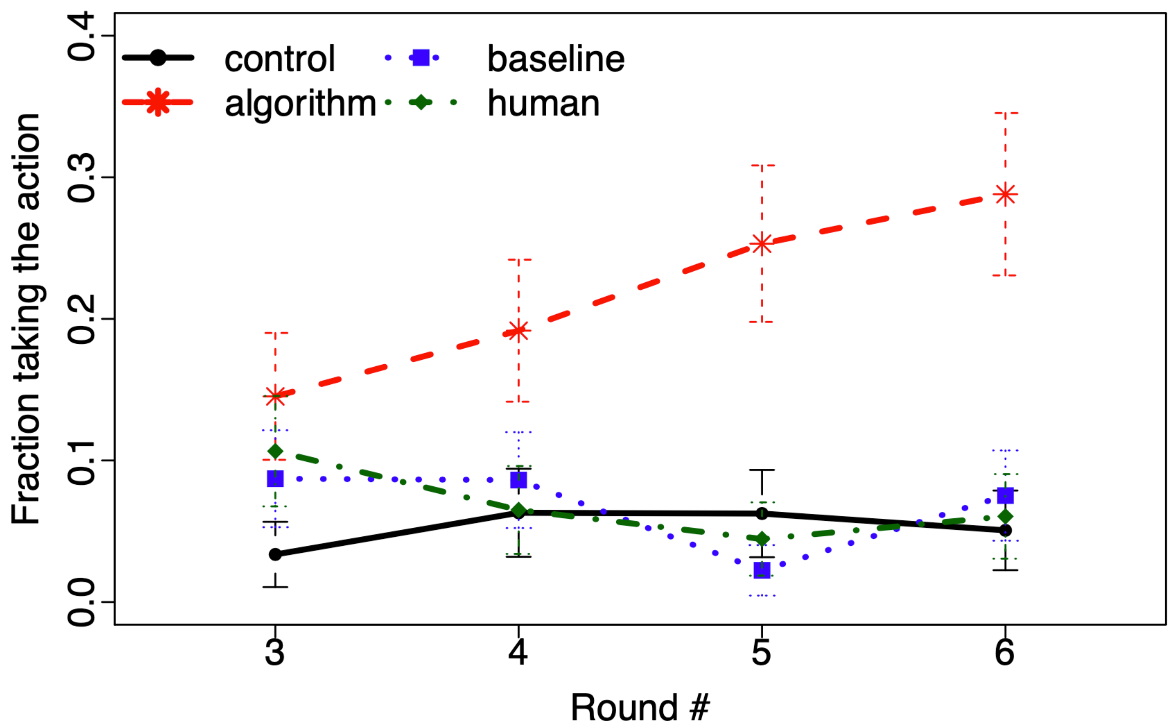
Results Learning Beyond Tips

Our tip effectively led people to the states they can learn other optimal strategies

Sous-Chef chops 3 times

↑

Part of optimal policy but not stated in any of the tips



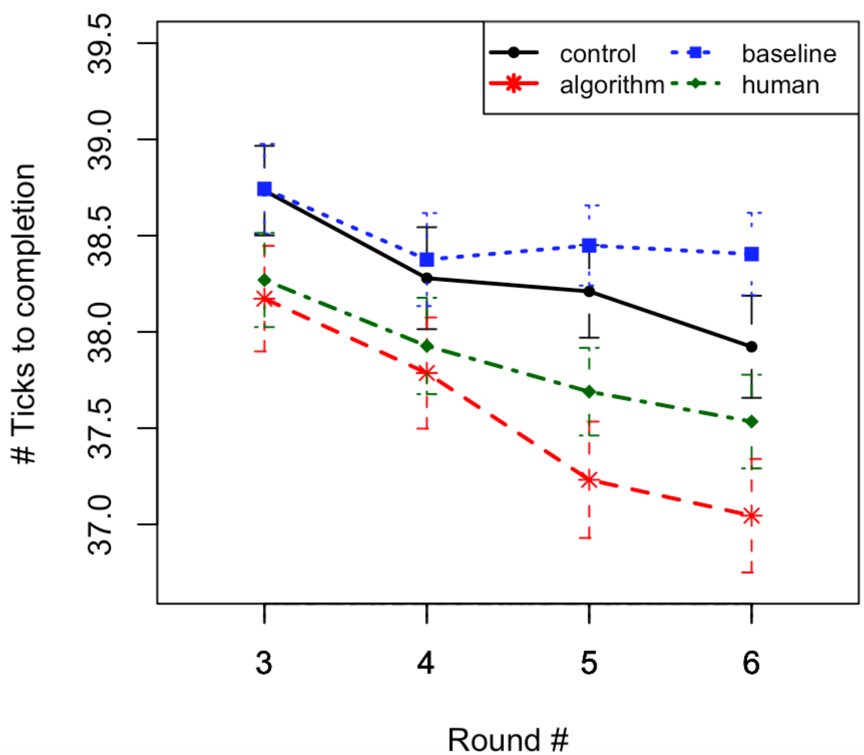
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

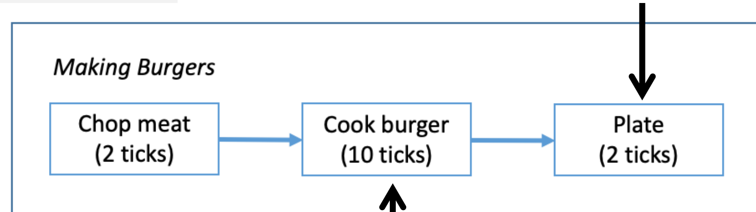
Study 1:

Results Good Tip = Consequential

Ticks to completion



Baseline Sous-Chef should plate twice



Algorithm Server should cook twice

Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Optimal Policies

Fully-staffed scenario: In this scenario, the participant has access to all three virtual workers. The optimal number of steps needed to complete this scenario is 20 ticks. The key insights to achieving optimal performance are: (i) all three workers should be assigned to chopping in the first time step, (ii) the chef must cook three of the burgers and the sous-chef must cook one (i.e., the second burger), (iii) the server should never cook and must be kept idle when the third burger becomes available for cooking; they should instead wait to be assigned to plating the first cooked burger, (iv) the chef should never plate, (v) the sous-chef must plate exactly one of the burgers, and (vi) none of the three workers should be left idle except in the previous cases.

Understaffed scenario: In this scenario, the participant has access to only two virtual workers—namely, the sous-chef and the server. The optimal number of steps needed to complete this scenario is 34 ticks. The keys insights to achieving the optimal performance are: (i) both workers should be assigned to chopping in the first time step, (ii) the sous-chef and the server must cook two burgers each, even though the server is very slow at cooking, (iii) the sous-chef must choose chopping over cooking after finishing her first chopping task, (iv) the server's first three tasks must be chopping, cooking, and cooking, in that order, (v) the sous-chef must chop three of the four burgers and the server must chop one, (vi) both workers must plate two burgers each, even though the sous-chef is slower at plating than the server, (vii) the second cooked burger must not be served until the third and fourth burgers are cooked, and (viii) both workers must be kept busy at all times.

Study 1:

Additional Results

	Phase I: Normal	Phase II: Normal	Phase I: Disrupted	Phase II: Disrupted
Total	183	1,317	172	1,011
Mean age [range]	34.6 [18, 76]	33.3 [18, 74]	34 [19, 76]	34.9 [16, 84]
Female	57.38%	51.03%	61.63%	60.14%
$\geq$ 2-year degree	73.22%	67.73%	77.91%	70.43%
Median duration	18.82 minutes	20.50 min	27.80 min	26.80 min
Found the game difficult	60.66%	50.04%	70.93%	64.99%
Never played similar games	45.36%	43.82%	46.51%	43.52%

Normal	Algorithm *"Chef shouldn't plate"*	Baseline *"Chef chops once"*	Human *"Leave some idle"*
(N1) Positive	25.87%	16.33%	29.23%
(N2) Negative	4.20%	5.44%	1.92%
(N3) Neutral	53.85%	51.70%	48.08%

Table 7: Participants' coded feedback on the provided tips (normal configuration).

Disrupted	Algorithm *"Server cooks twice"*	Baseline *"Sous-chef plates twice"*	Human *"Server cooks once"*
(D1) Positive	23.10%	10.19%	25.87%
(D2) Negative	33.10%	37.58%	16.78%
(D3) Neutral	32.76%	42.99%	47.90%

Table 8: Participants' coded feedback on the provided tips (disrupted configuration).

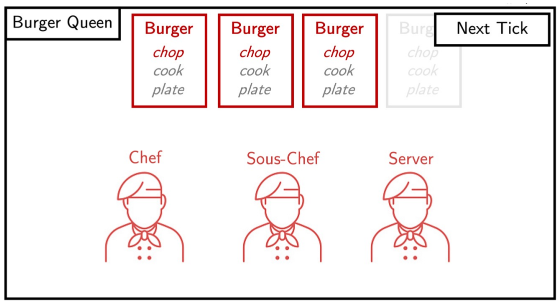
User Study Design

N = 1400

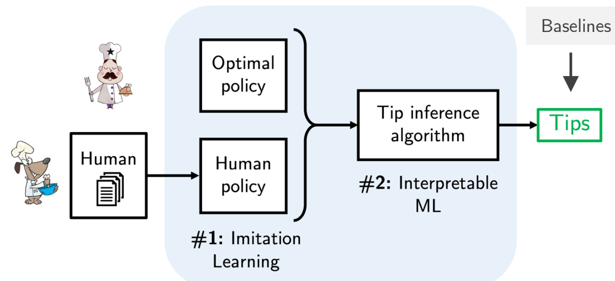
Phase I

N = 200

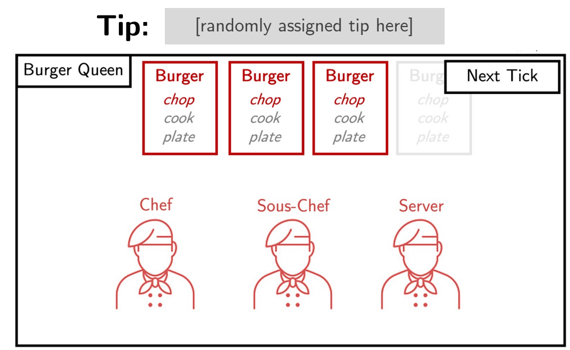
Phase II



Gather trace data



Tip inference



Tip evaluation

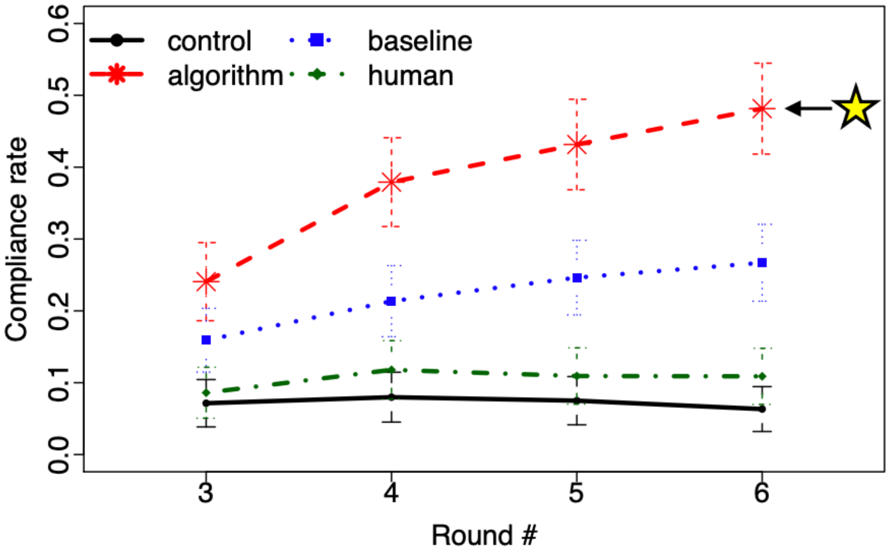
Environment

Normal

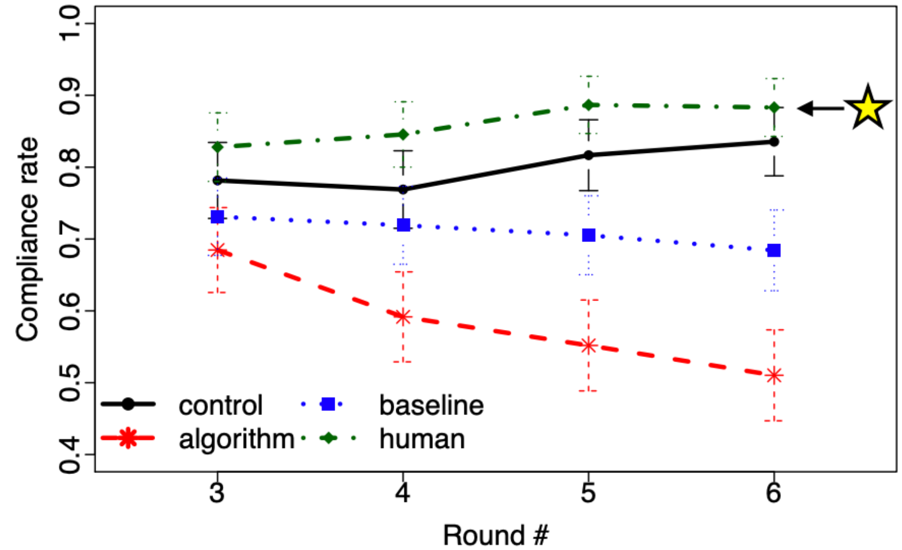
Disrupted

in the middle

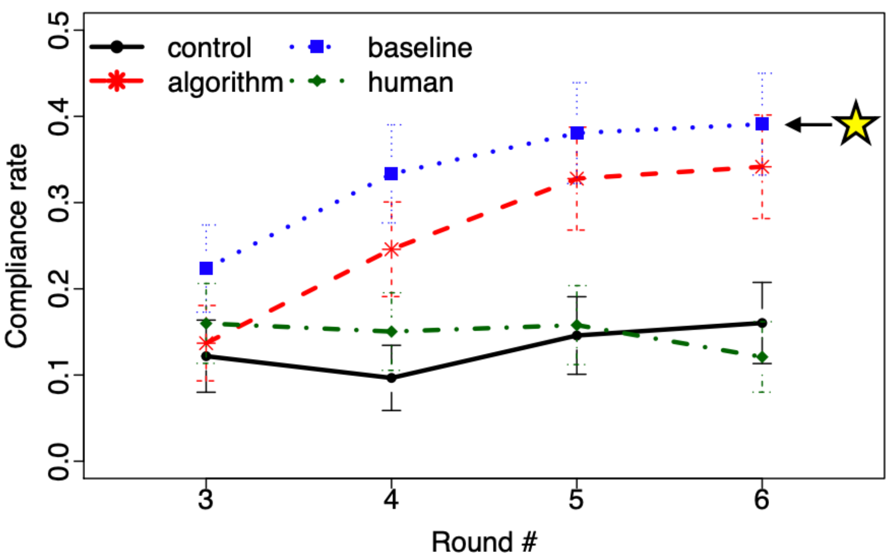
Pre-registered at https://aspredicted.org/blind.php?x=8ye5cb



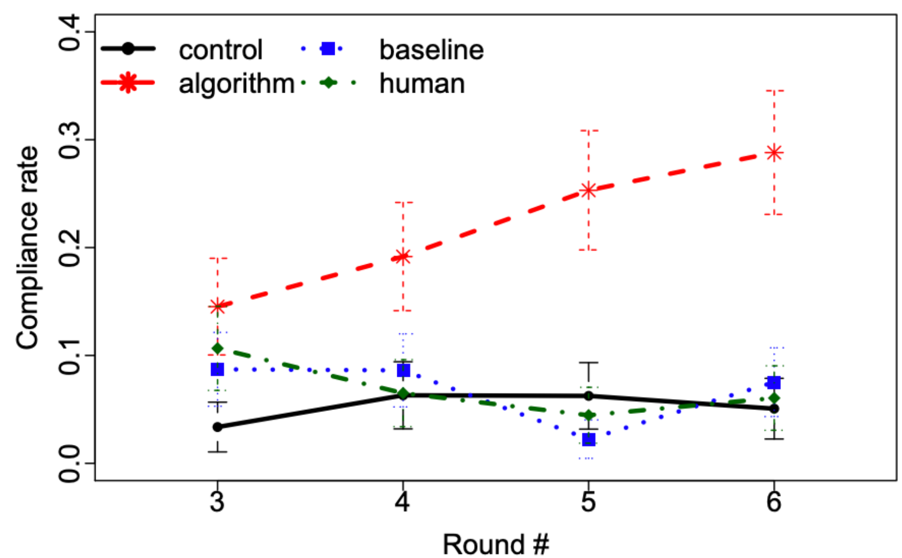
(a) Algorithm Tip: "Server cooks twice"



(b) Human Tip: "Server cooks once"

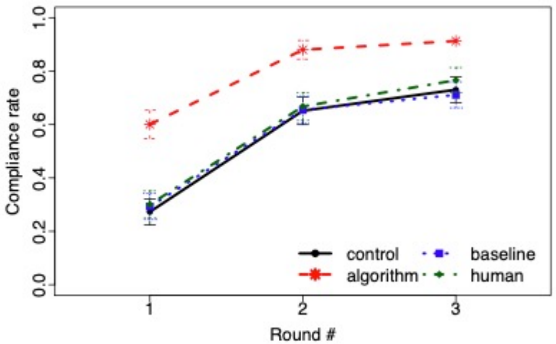


(c) Baseline Tip: "Sous-chef plates twice"

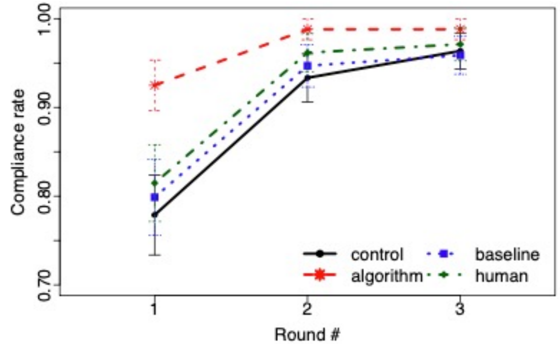


(d) Unshown Tip: "Server chops once"

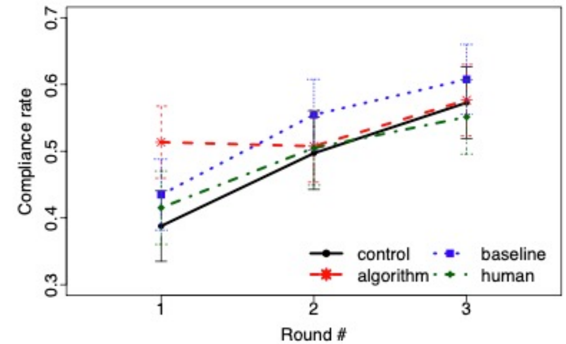
Learning Beyond Tips



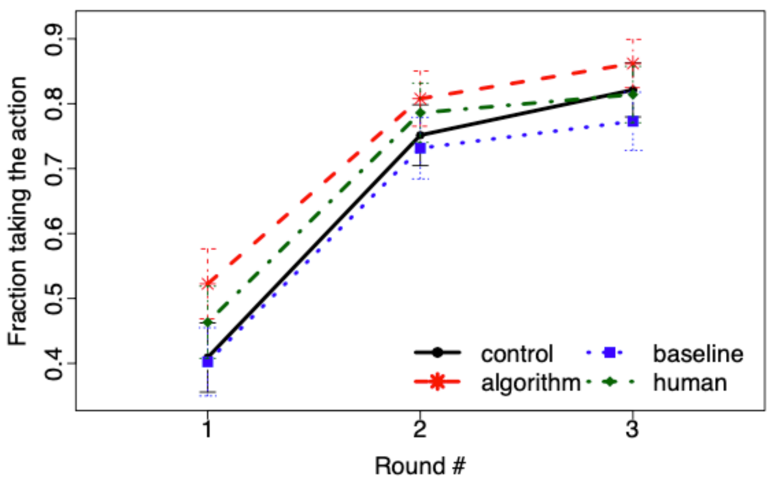
(a) Algorithm: "Chef shouldn't plate"



(b) Human: "Leave some idle"



(c) Baseline: "Chef chops once"



(a) Fully-staffed: "Server shouldn't cook"

Study 2:

What If Decisions Are More Granular?

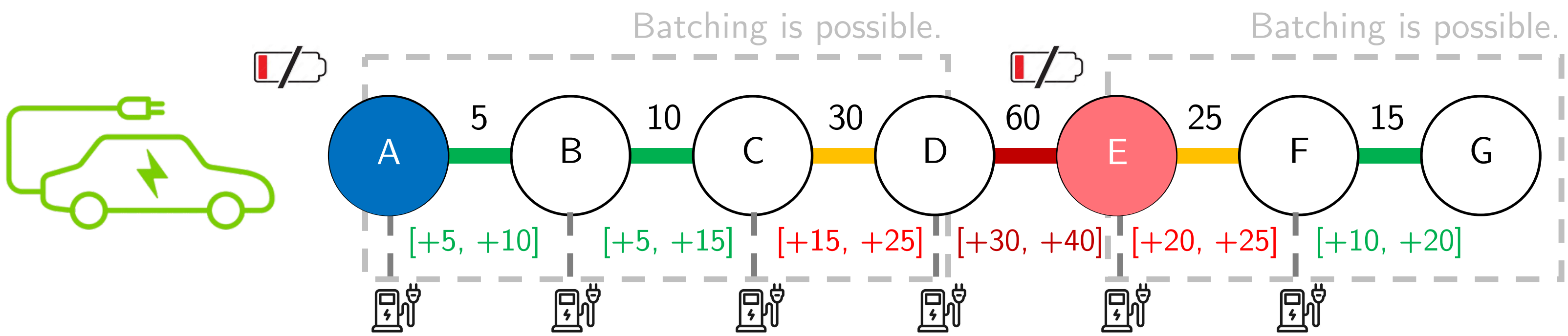
Also, What If Things Are Uncertain?

Sequential	To arrive fast, min travel + charging times
Complex	Non-linear charging, fixed vs variable cost
Uncertain	Uncertain traffic, risk-preferences
Continuous	Anything from 0-100%, all-or-nothing/charge to full suboptimal

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design Flow

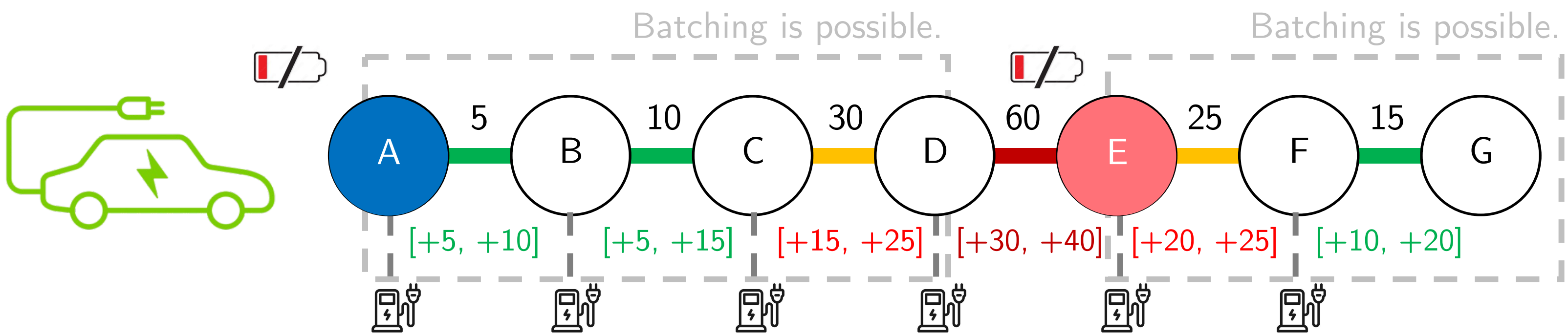


Performance: Time to destination

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design Flow



Performance: Time to destination

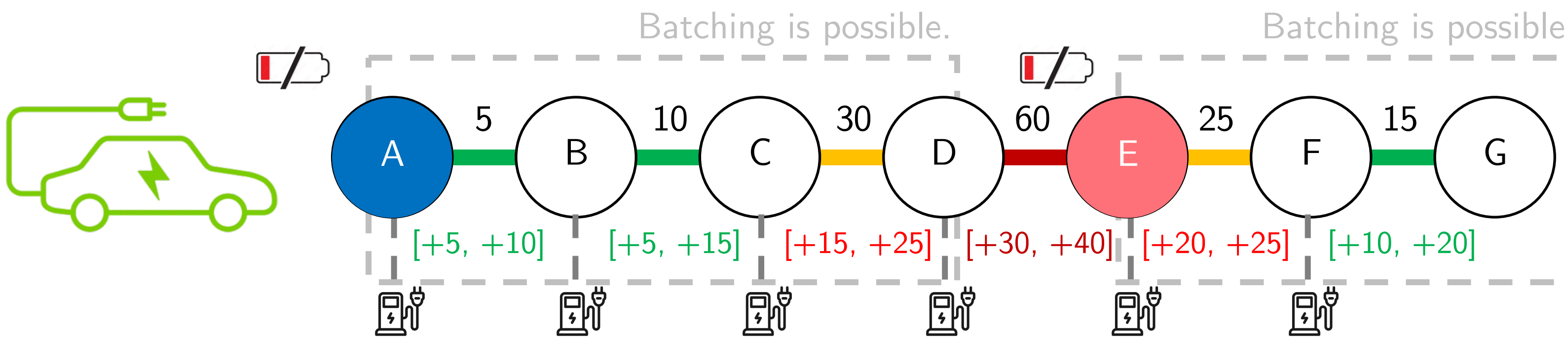
Round 1	Round 2

Realized traffic will be different across rounds but drawn from the same distributions

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design Flow



Performance: Time to destination

Round 1	Round 2	Round 3 (+ tip)	Round 4 (+ tip)

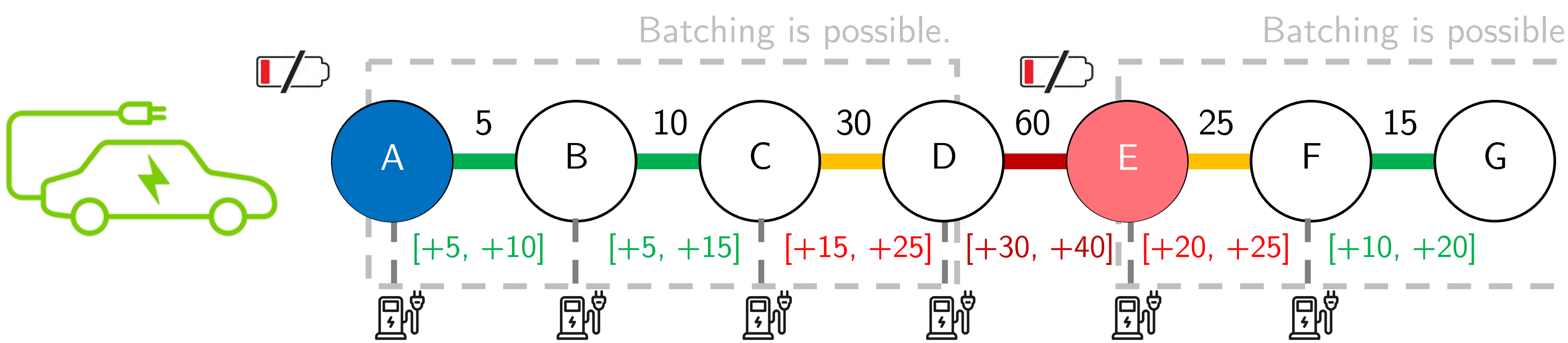
Realized traffic will be different across rounds but drawn from the same distributions

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design

Tip Conditions: *Precise vs Broad*



Performance: Time to destination

Round 1	Round 2	Round 3 (+ tip)	Round 4 (+ tip)

Realized traffic will be different across rounds but drawn from the same distributions

At every stop, we present either...

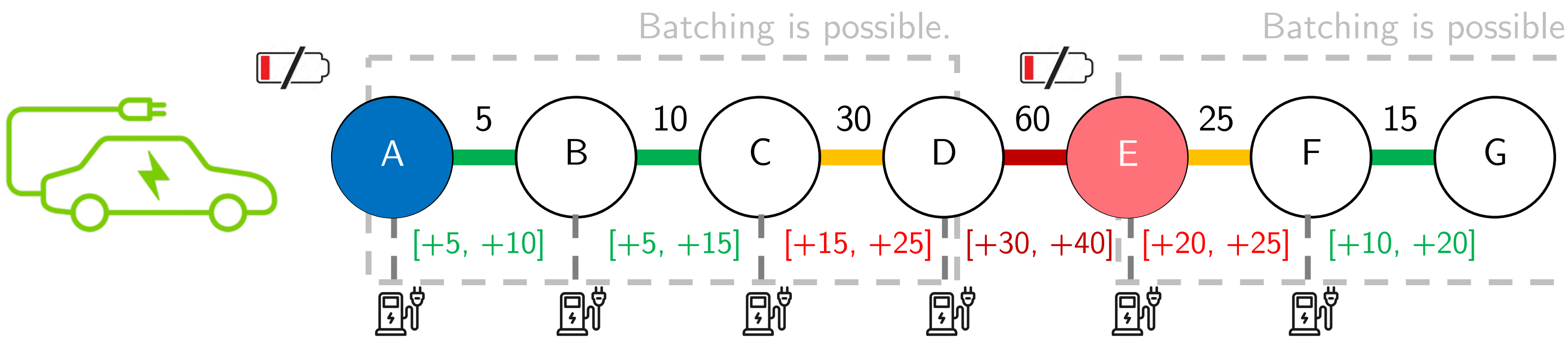
Precise Tip:

You should exit and charge X%

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design Tip Conditions: *Precise vs Broad*



Performance: Time to destination

Round 1	Round 2	Round 3 (+ tip)	Round 4 (+ tip)

Realized traffic will be different across rounds but drawn from the same distributions

At every stop, we present either...

Precise Tip:

You should exit and charge X%

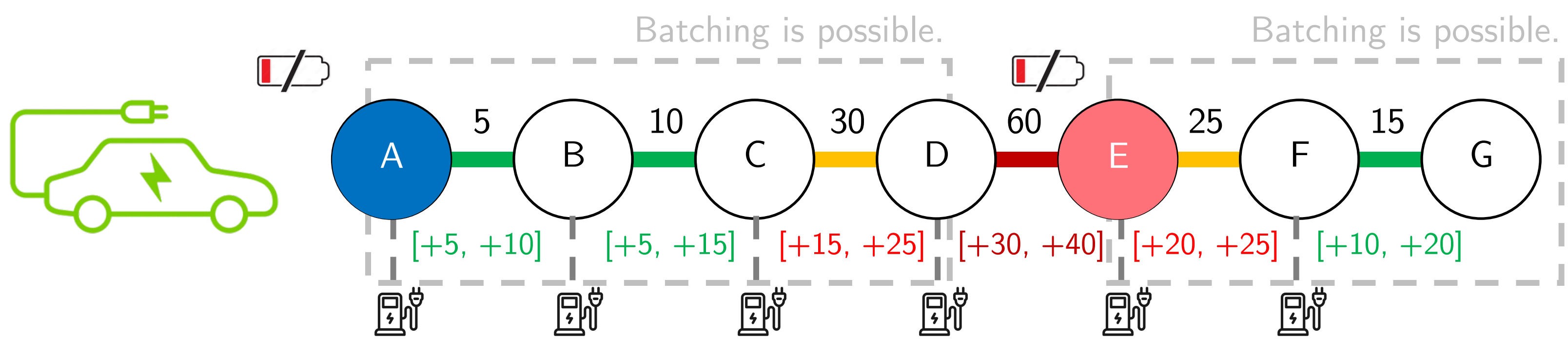
Broad Tip:

"Split" You should charge enough for this segment

Pre-registered at https://aspredicted.org/7LP_J9G

Study 2A:

Design Tip Conditions: *Precise vs Broad*



Performance: Time to destination

Round 1

Round 2

Round 3 (+ tip)

Round 4 (+ tip)

Realized traffic will be different across rounds but drawn from the same distributions

At every stop, we present either...

Precise Tip:

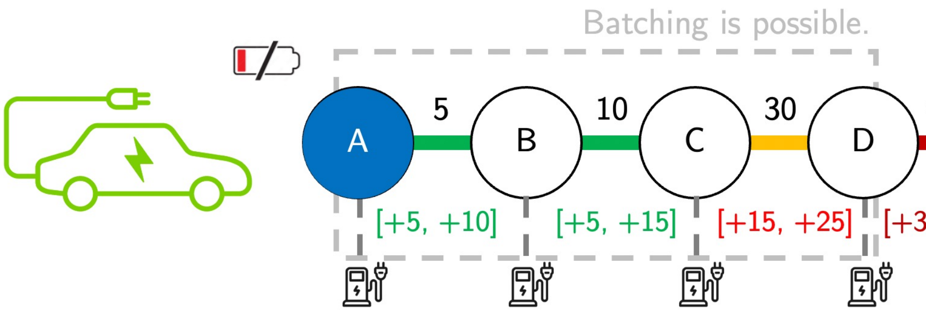
You should exit and charge X%

Broad Tip:

"Split" You should charge enough for this segment

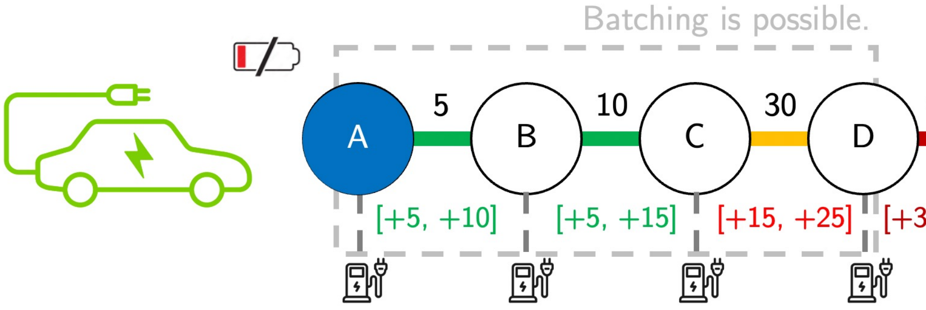
"Batch" You should charge enough for this segment + next one

Study 2A:
Results



Exit A: Forced to charge
Optimal: Batch A → C
rather than just A→B
or further batch A→D.
("aftercharge" = 25-40)

Study 2A:
Results



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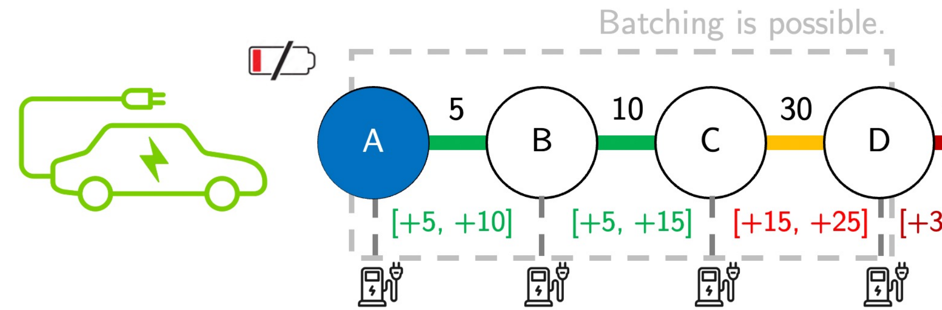
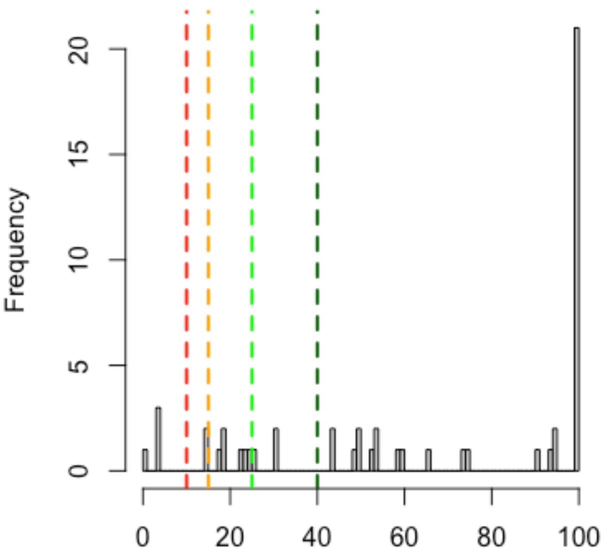
Aftercharge
= amount of charge after re-charging

Study 2A:

Results Wide Range of Decisions



Round 1



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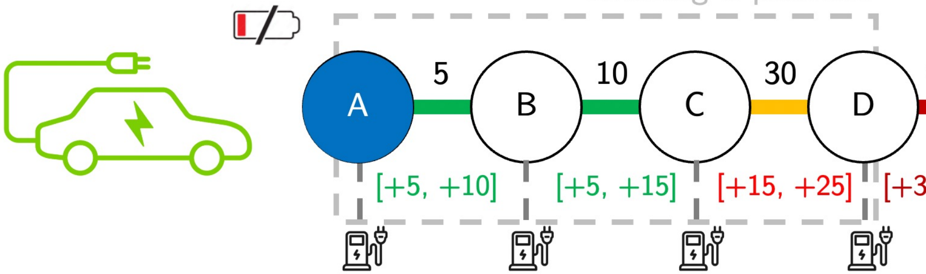

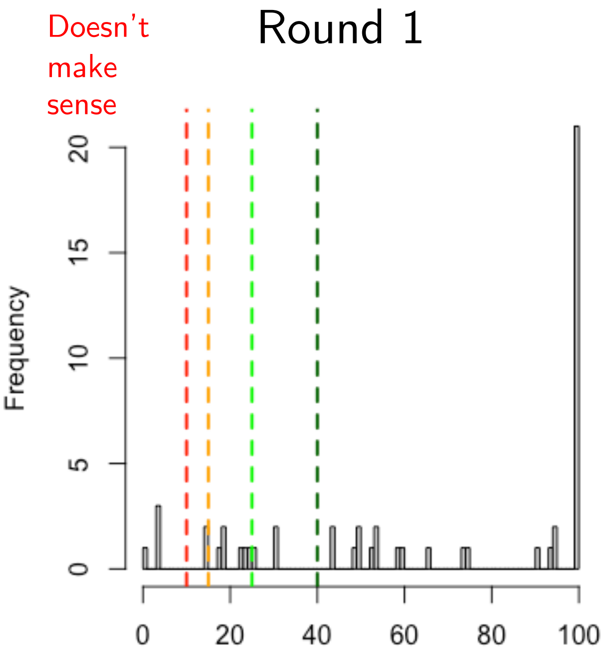

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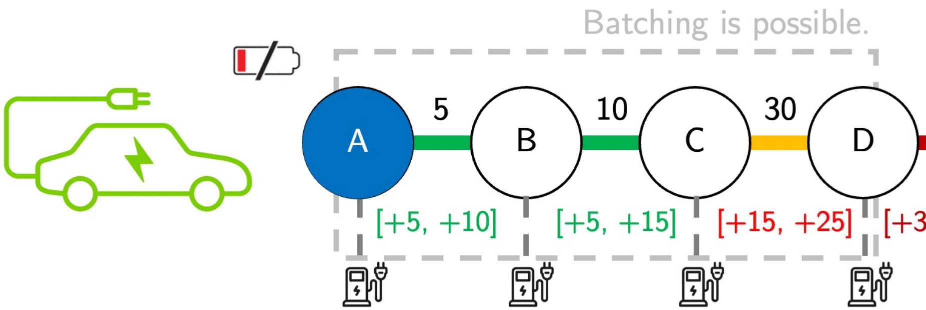

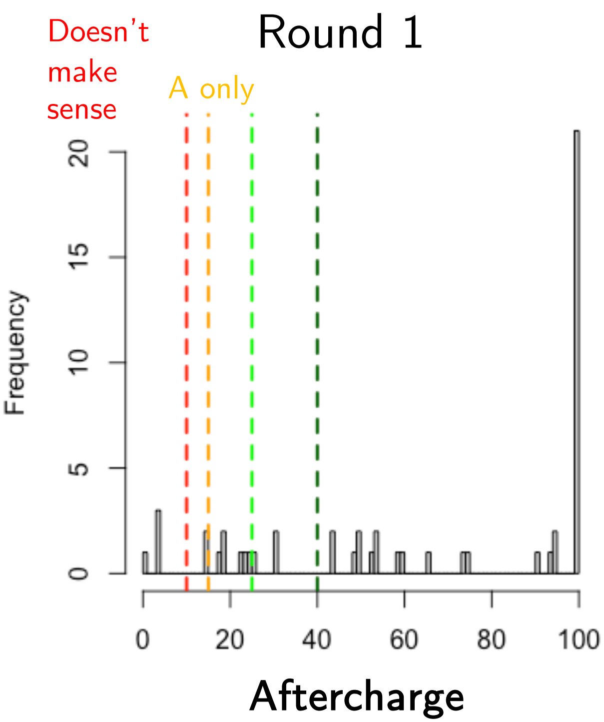

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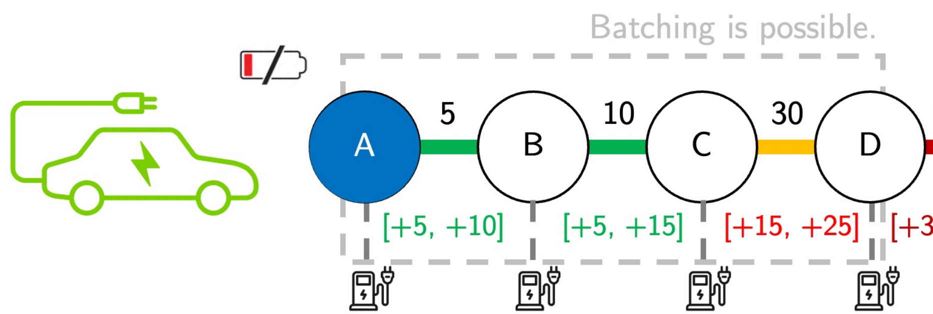

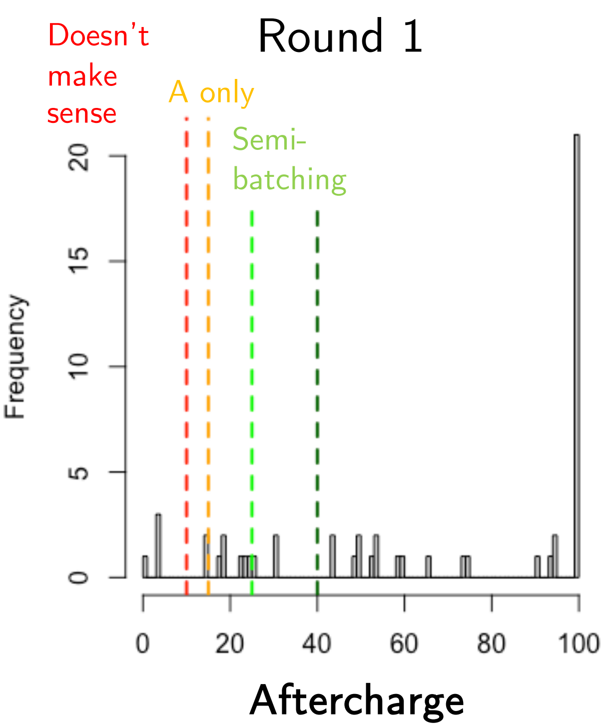

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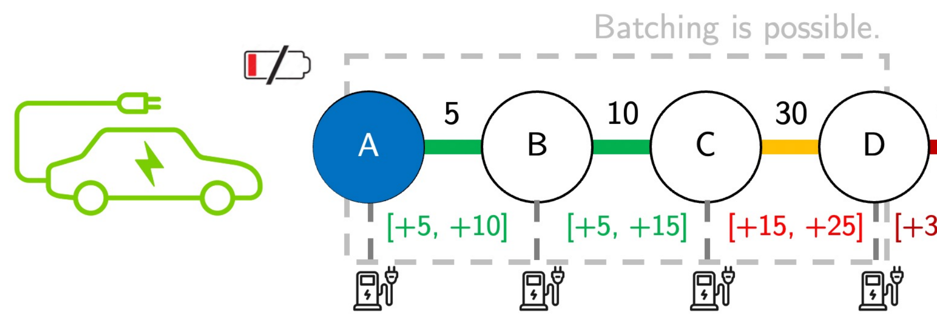

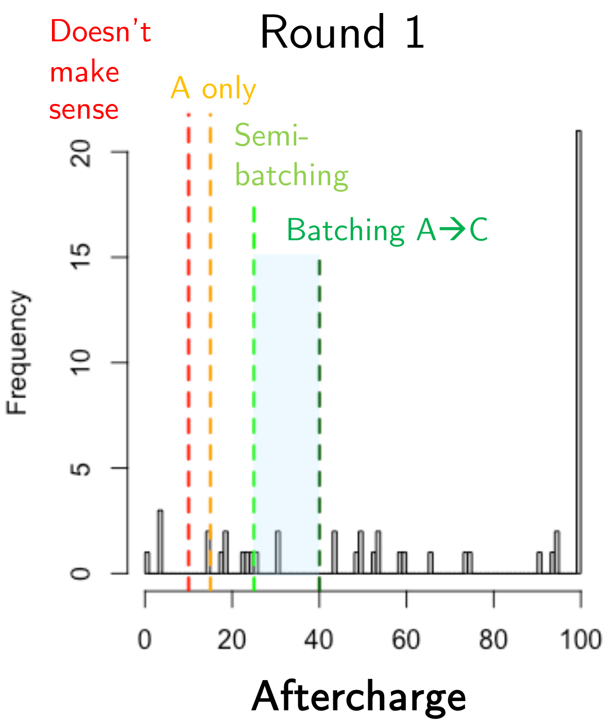

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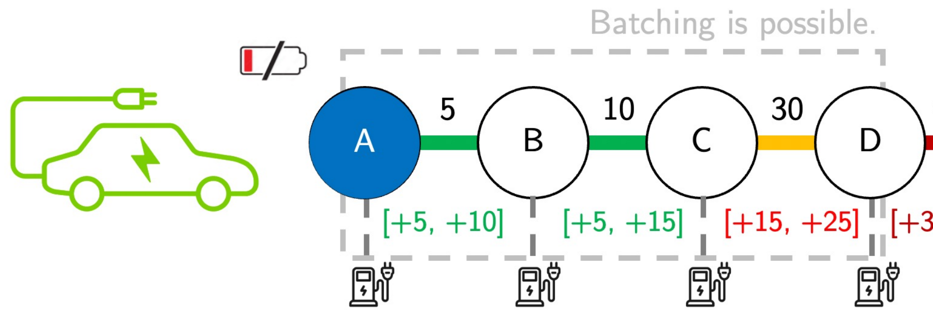

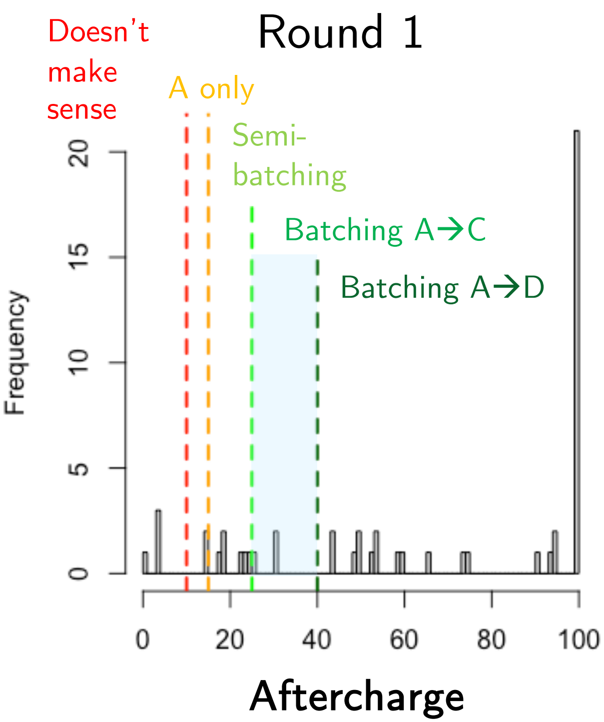

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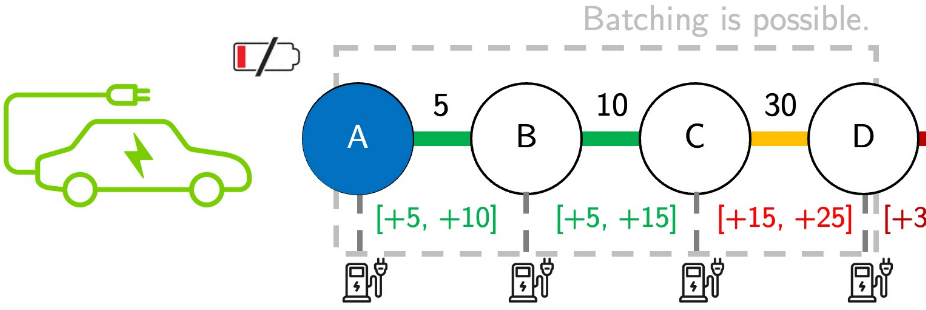

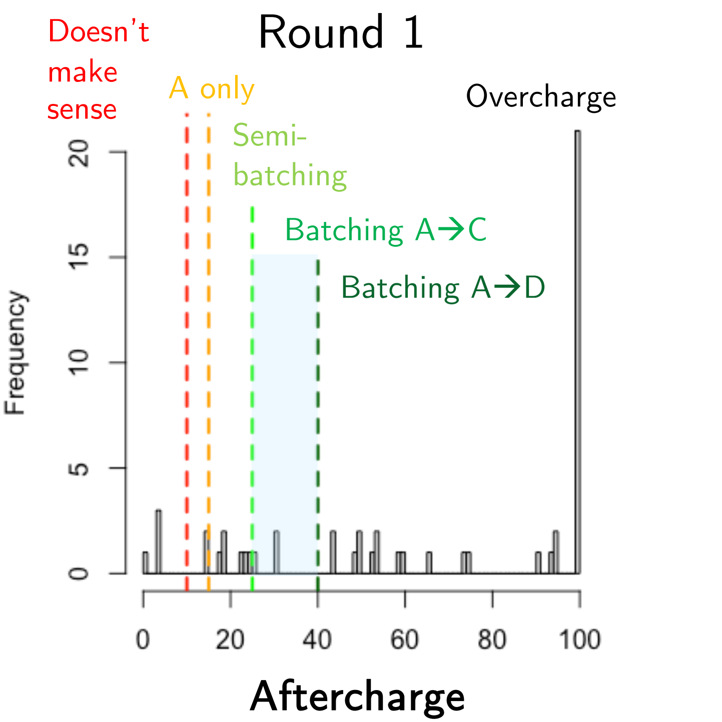

= amount of charge after re-charging

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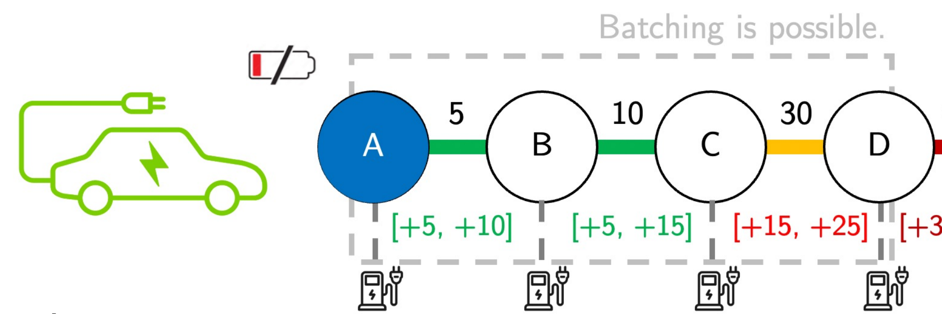
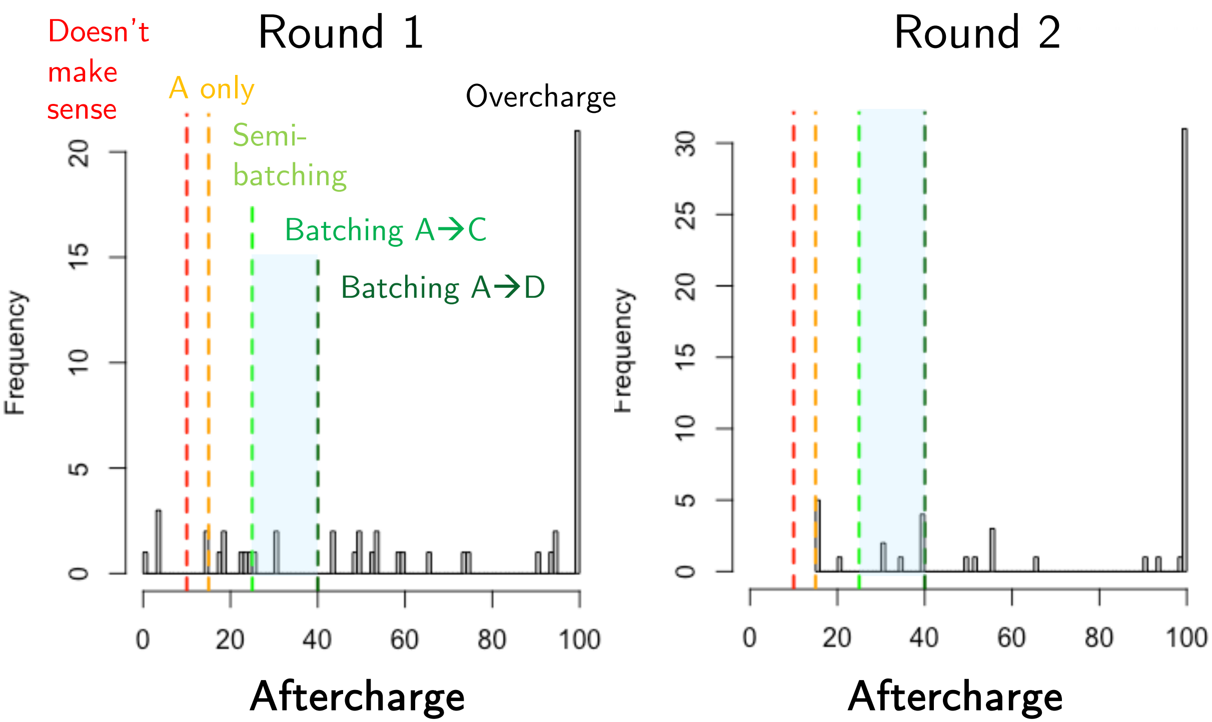
Study 2A:

Results People Learned w/o Tip





= amount of charge after re-charging

Exit A: Forced to charge
Optimal: Batch A → C
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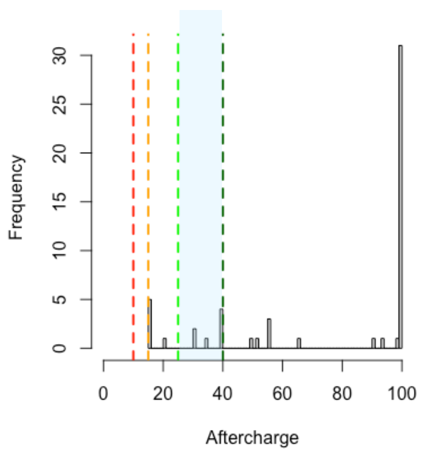
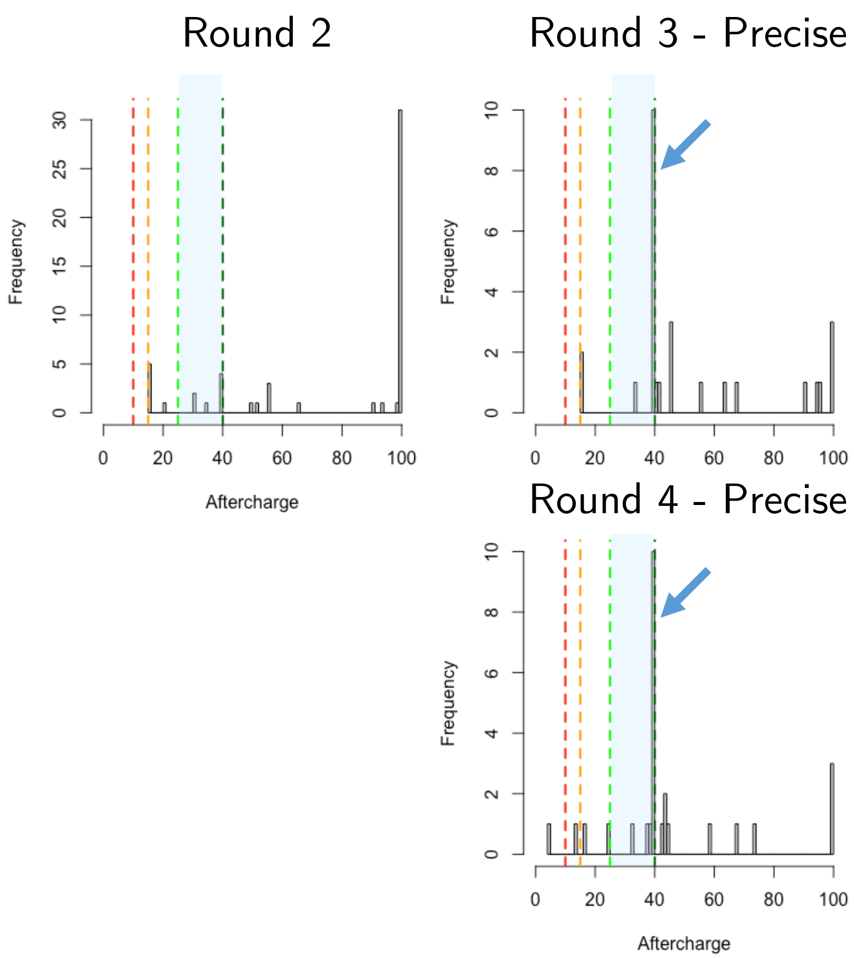
In one round, everyone learned to do at least semi-batching for this exit.

Results What Happened with Tip?

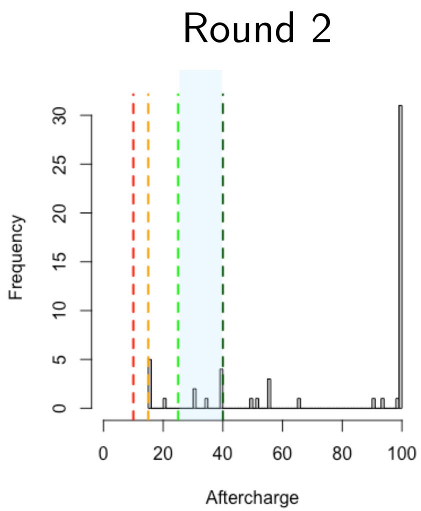
Round 2

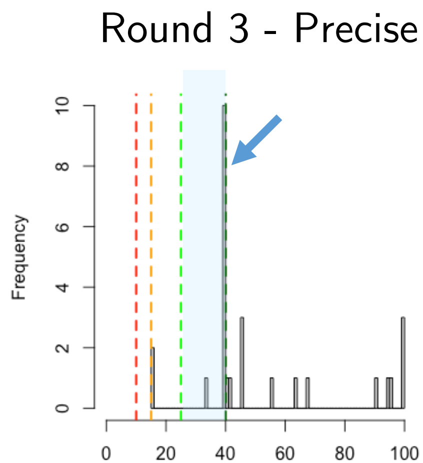


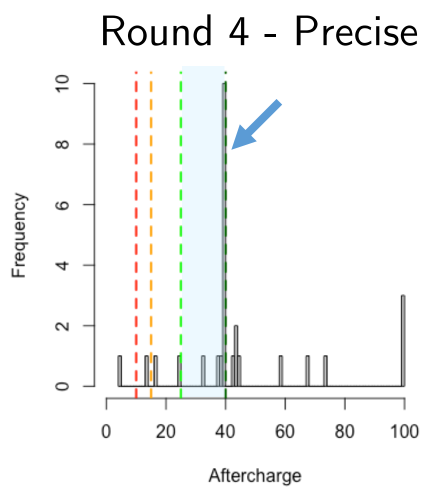
Results


Round 2
Round 3 - Precise
Round 4 - Precise
Frequency
Aftercharge
0
20
40
60
80
100
5
10
15
25
30
2
4
6
8

Results Precise Tip Worked (as Expected)



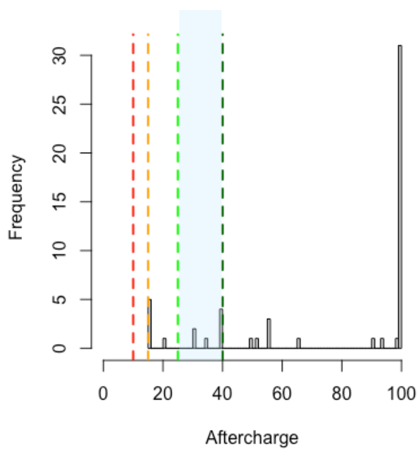




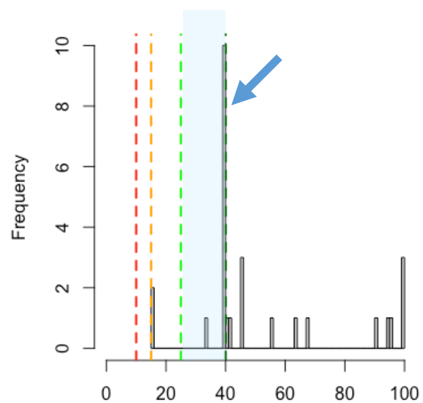
The **Precise** tip successfully nudged participants to batch A → C

Results

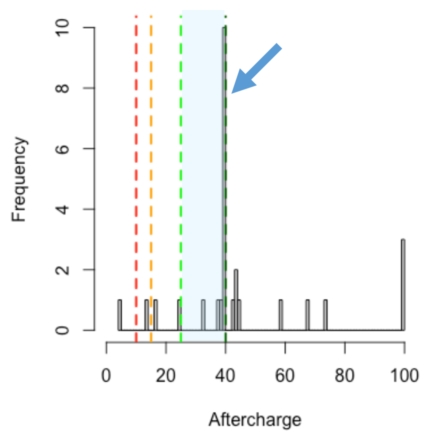
Round 2



Round 3 - Precise



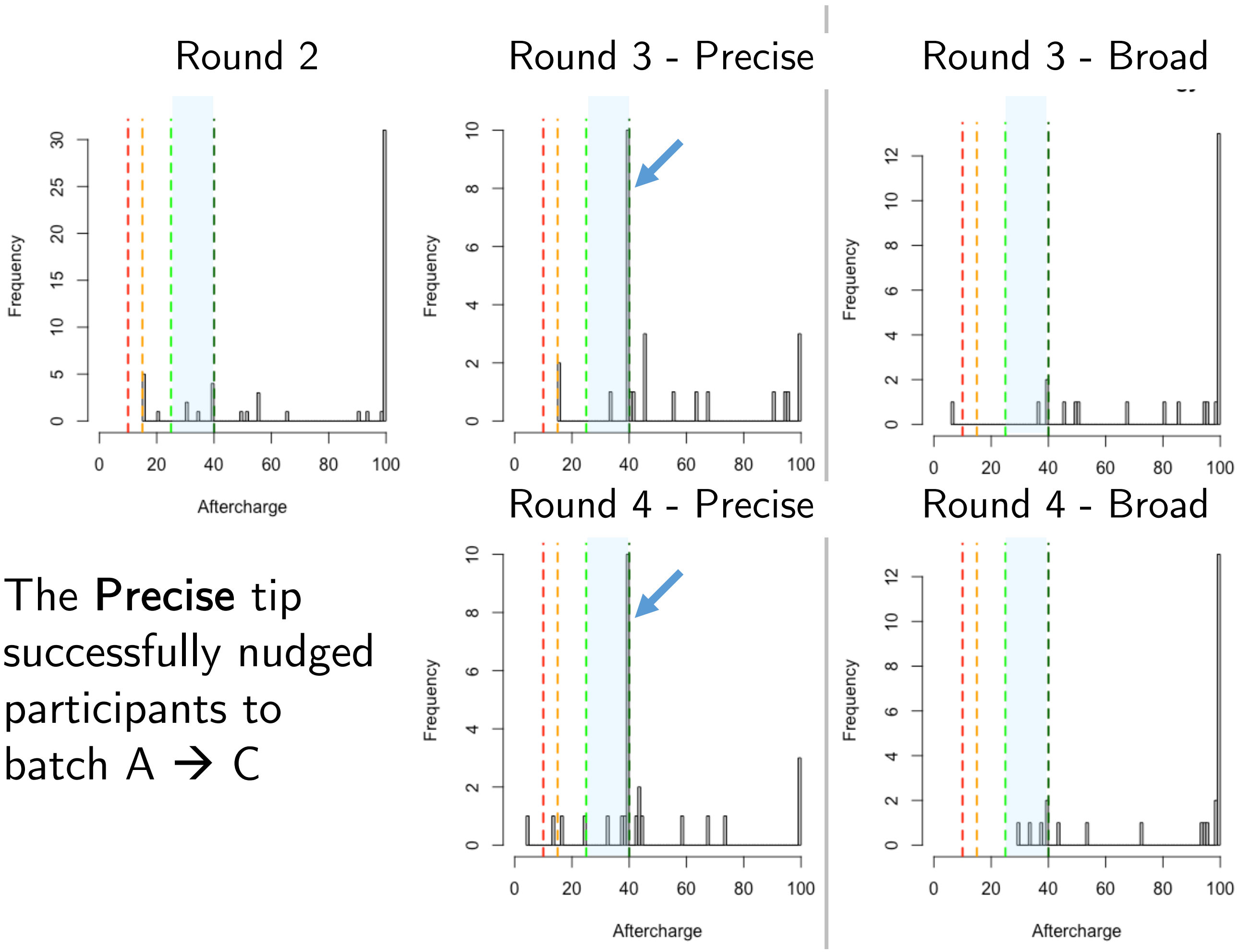
Round 4 - Precise



The **Precise** tip successfully nudged participants to batch A → C

Broad tip
"You should charge enough for this segment and the next one"

Results Broad Tip Kind of Failed

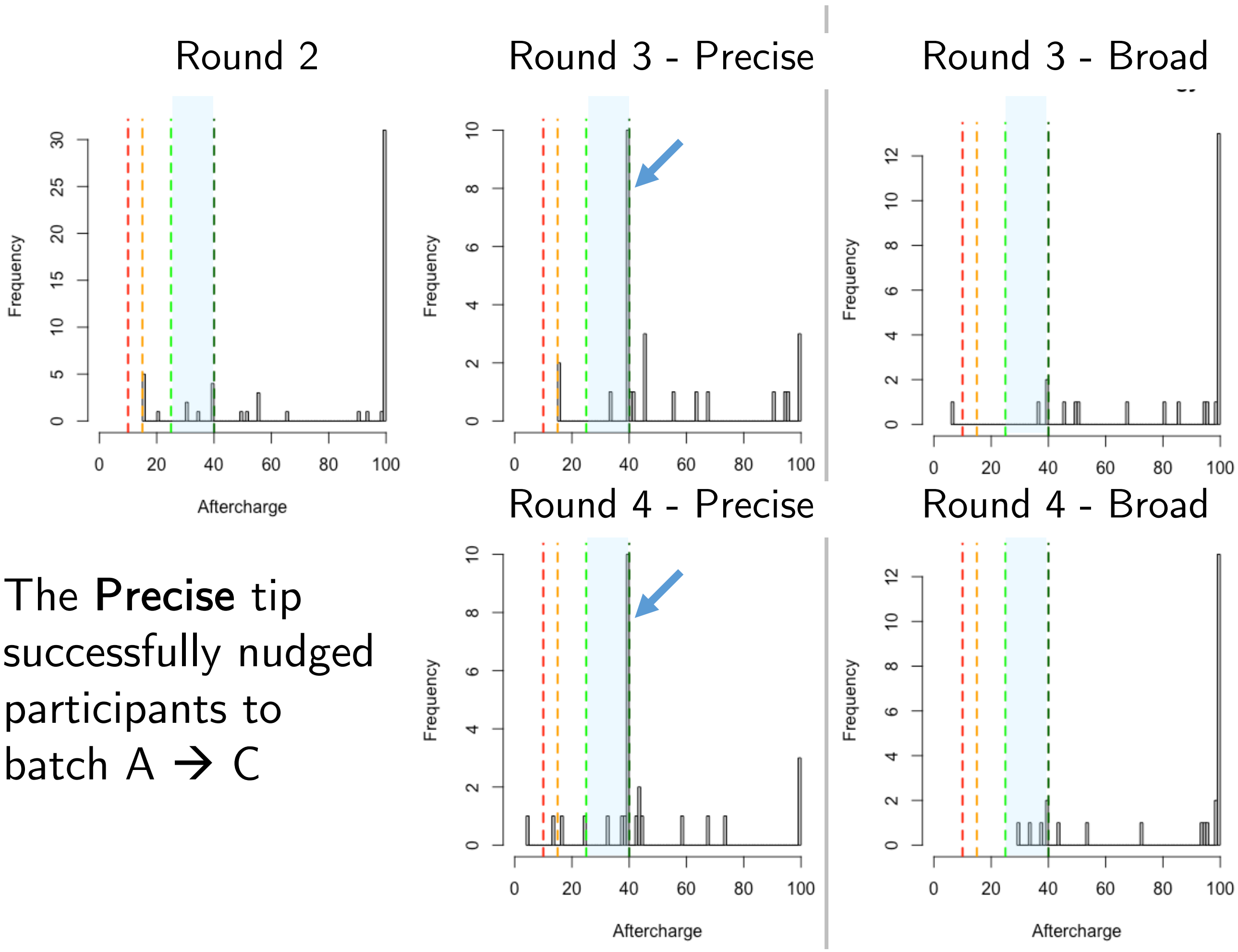


Broad tip
"You should charge enough for this segment and the next one"

The **Broad** tip had low compliance even though it was clear what the participant should do

The **Precise** tip successfully nudged participants to batch A → C

Results Broad Tip Kind of Failed



Broad tip
"You should charge enough for this segment and the next one"

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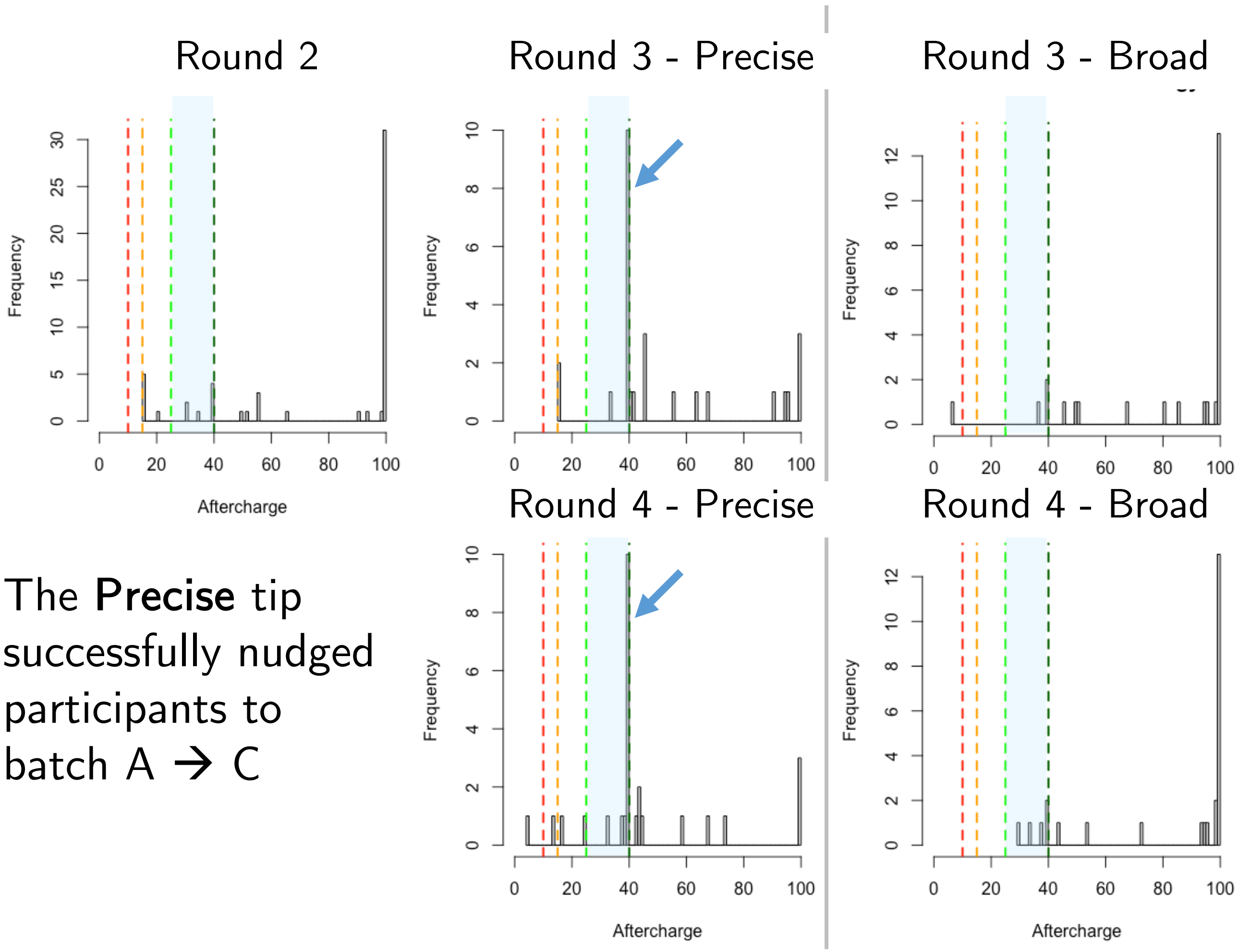
Q: Could it be due to the tip being perceived as counterintuitive?

Results Broad Tip Kind of Failed



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The **Broad** tip had low compliance even though it was clear what the participant should do

The **Precise** tip successfully nudged participants to batch A → C

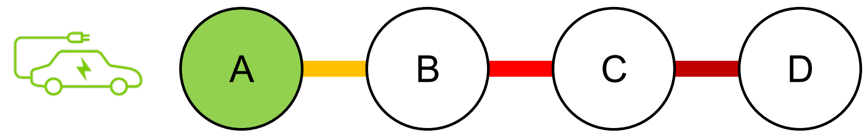
Q: Could it be due to the tip being perceived as counterintuitive?

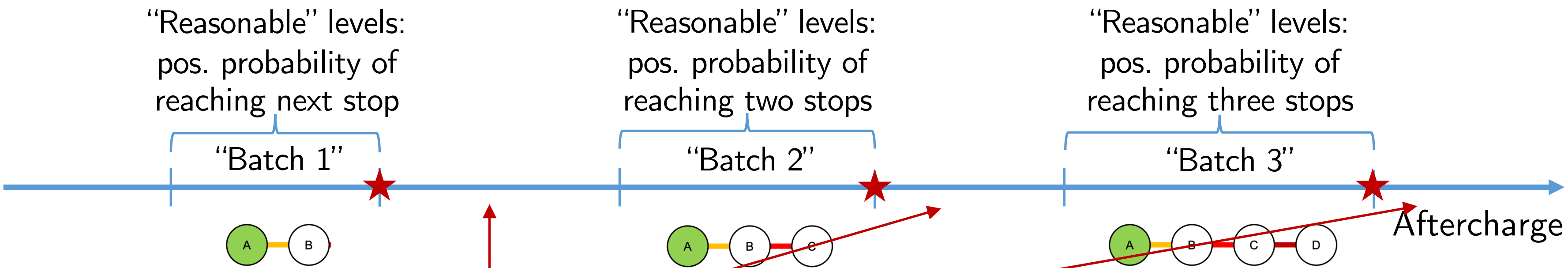
Q: Did Precise tip help people learn?

But Did We Help Them

Improve Their Decision-Making?

Classifying Decisions

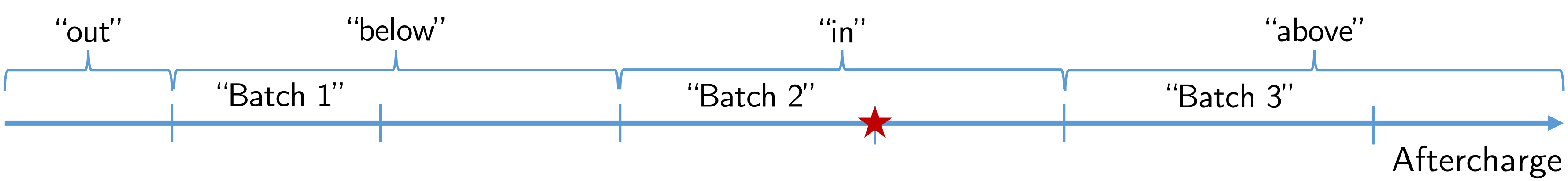




Too little charge for next "batch",
but too much for current…
…but **most charging here**
(risk aversion, limited look-ahead)
→ unnecessarily conservative

Hierarchical model of decision-making:

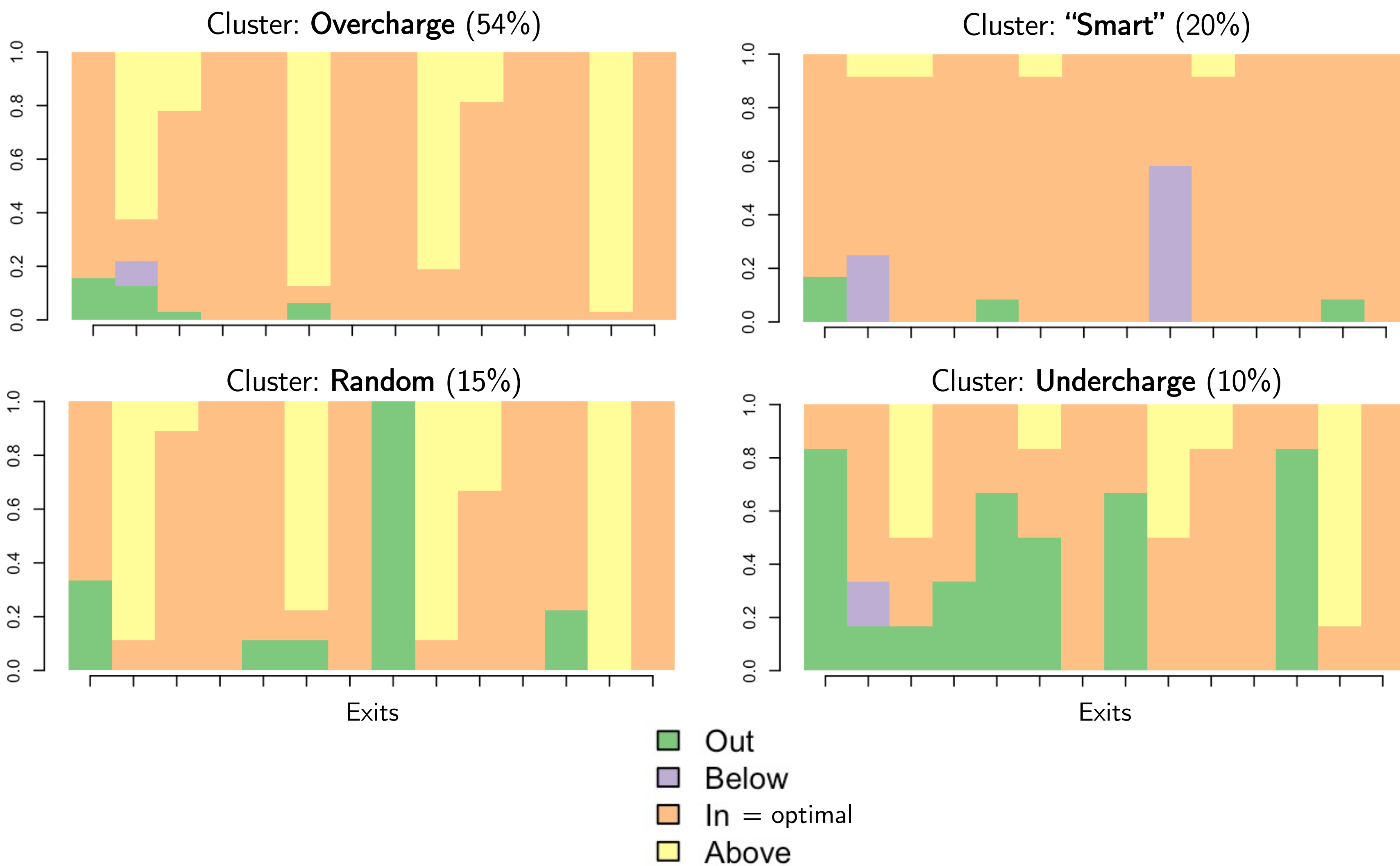
1. Choice of broad interval
2. Choice of charge within interval



→ Consistent choice of intervals as an indicator of strategic behavior

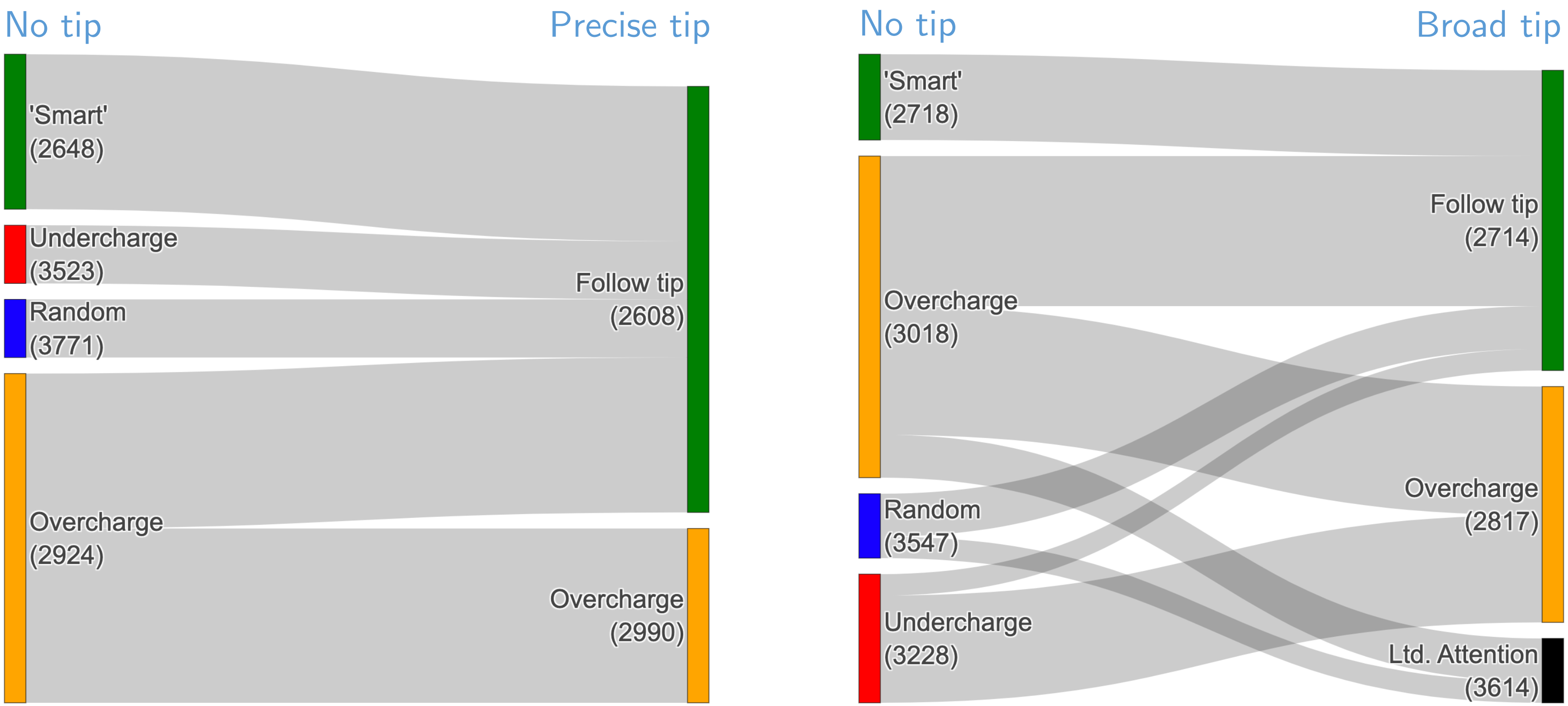
Study 2A:

Results Clustering Pre-Tip Behaviors



Study 2A:

Results Predicting Response to Tip



→ Advice followed exactly or more conservatively

→ Precise advice followed more

→ "Smart" behavior is good indicator of "converting" imprecise tips