Improving Human Decision-Making with Machine Learning

Park Sinchaisri
UC Berkeley Haas

MIT IDE Lunch Seminar
November 15, 2023

Learning is Costly

2+ years

to be fully productive

$1,286/worker

training expenses

- Training Magazine 2019

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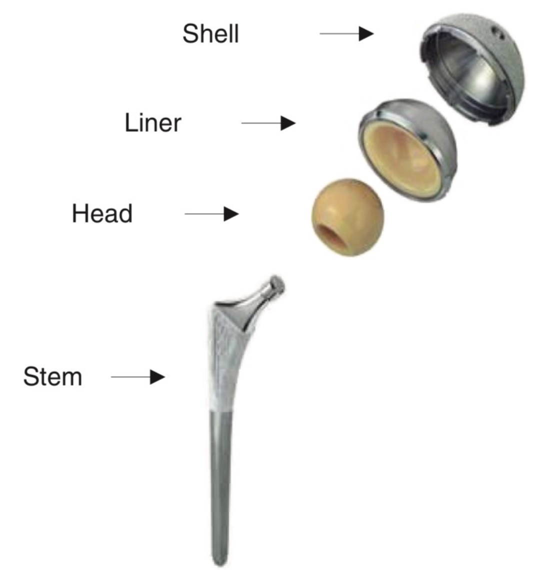
Hip replacement surgery



New device = **+32.4%**

surgery duration

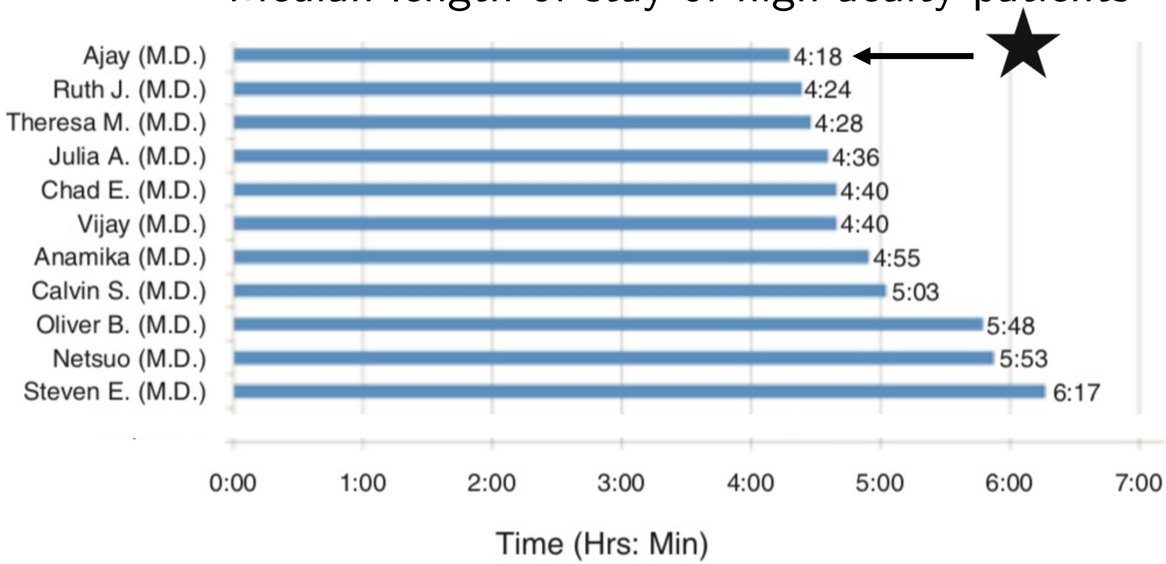
- Ramdas et al. 2018

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

Learning from Experts

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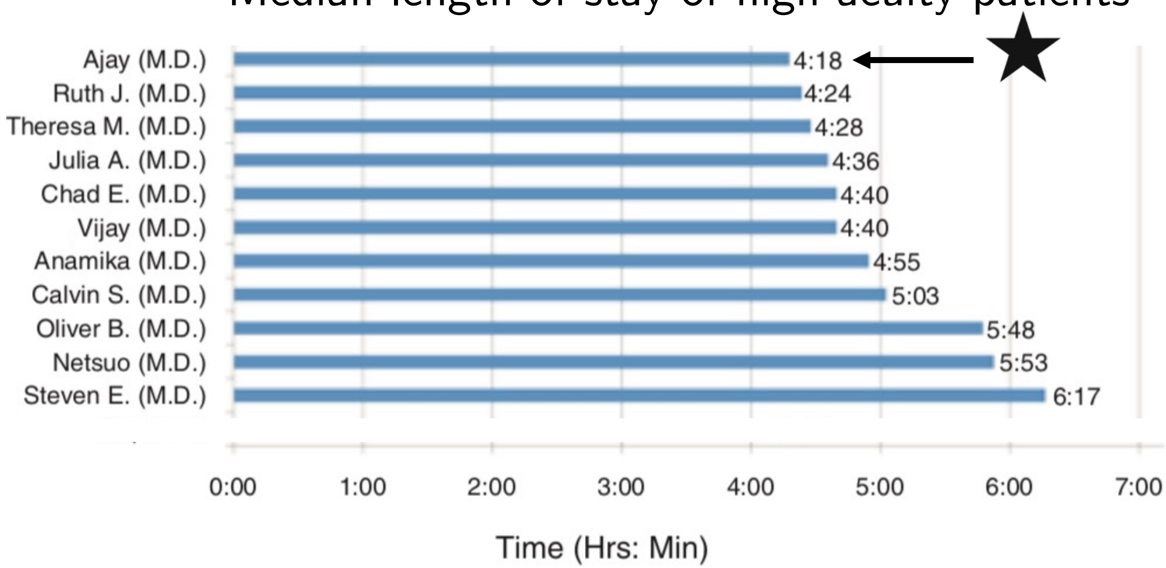


+10.9%

productivity

- Song et al. 2018

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

Learning from Experts

Median length of stay of high acuity patients

+10.9%

productivity

- Song et al. 2018

Learning from Experts

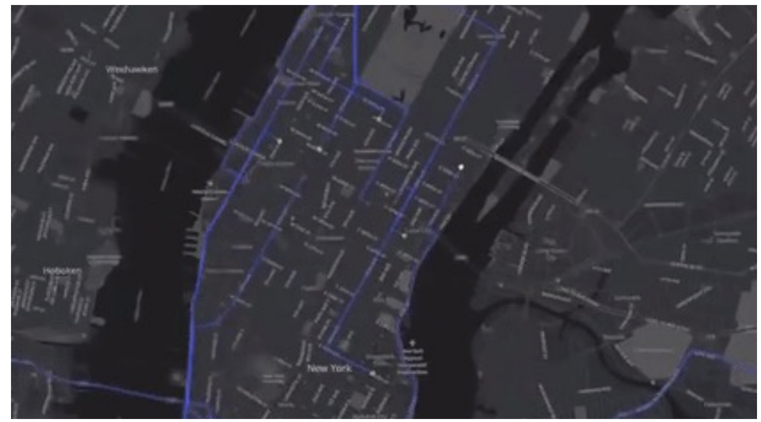
+10.9%
productivity
- Song et al. 2018

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



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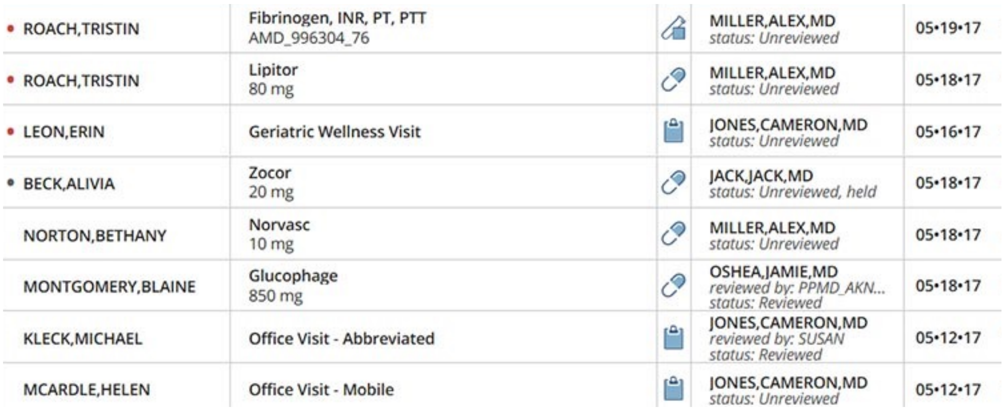

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Uber Drivers

Trace data → Tips

Trace Data is Everywhere

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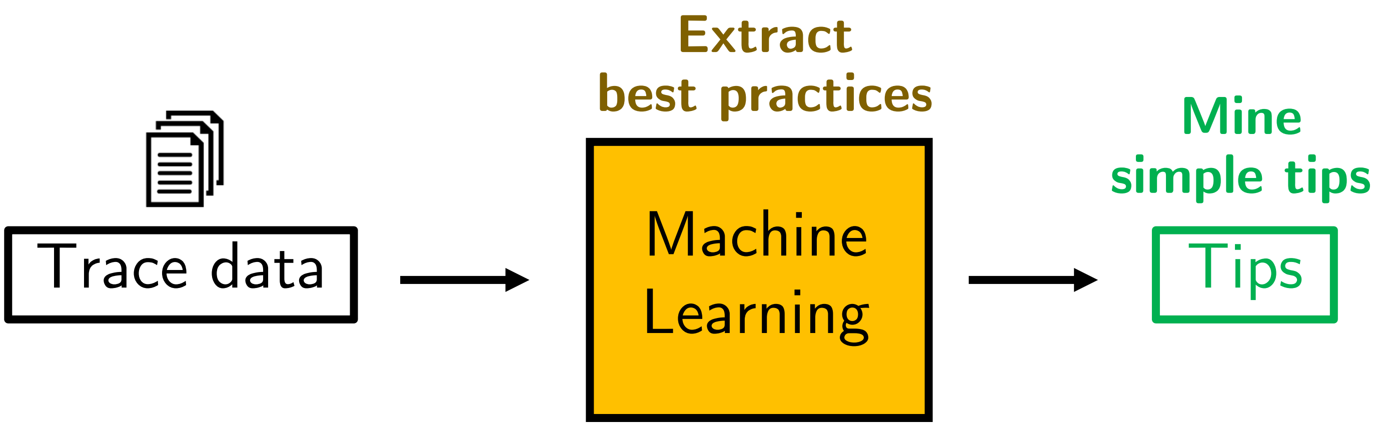

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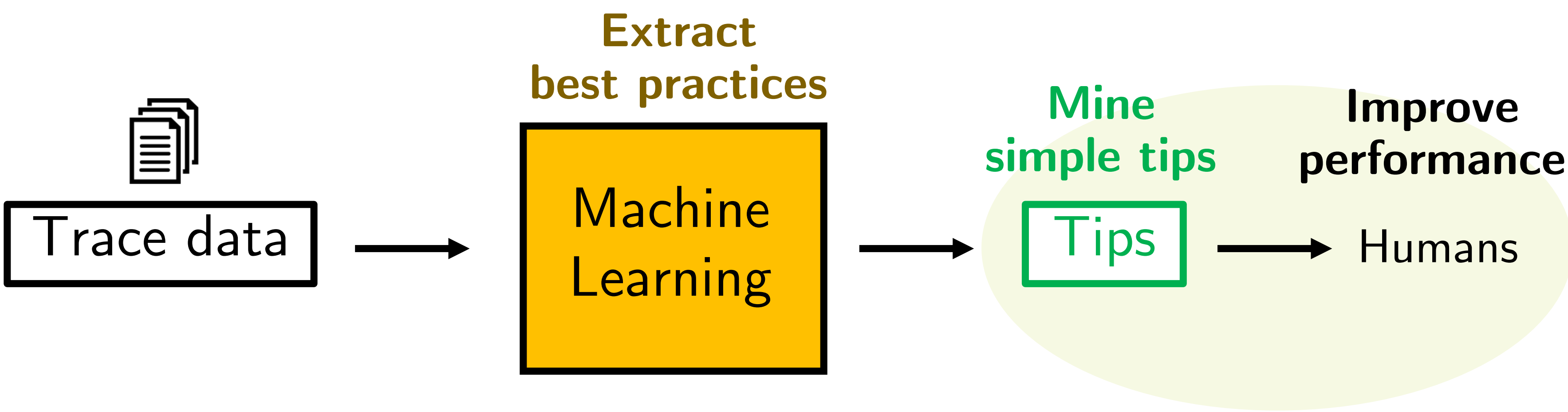
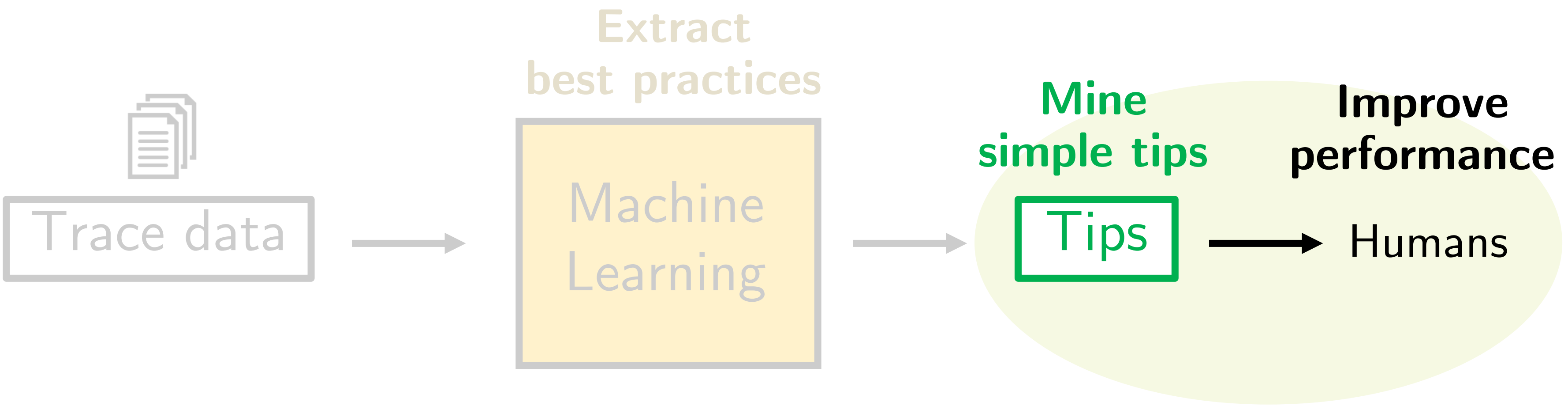
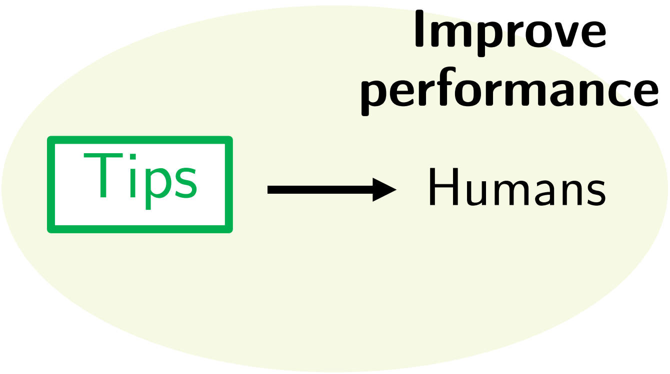


Potential Issues



Potential Issues

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



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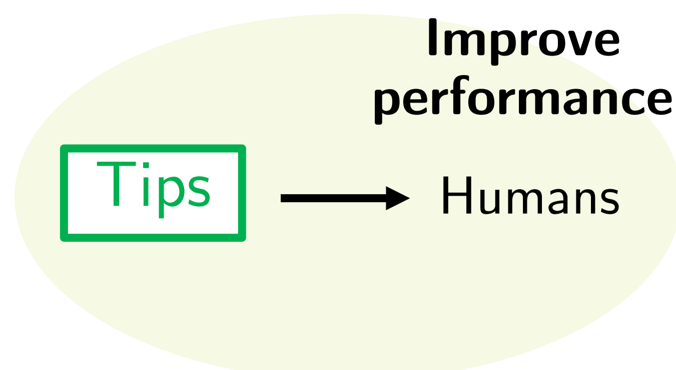
BUSINESS

Will the public accept the fatal mistakes of self-driving cars?

By Steven Overly

February 20, 2017 at 6:48 p.m. EST



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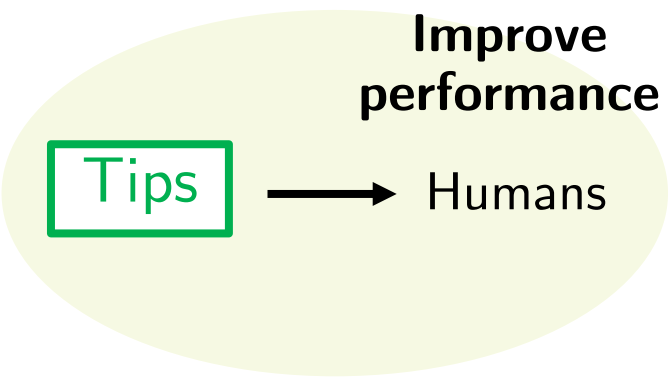
- Private information (e.g., Ibanez et al 2018, Balakrishnan et al 2022, Sun et al 2022)



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Improve performance

$\boxed{\text{Tips}} \longrightarrow$ Humans

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Fashion

Make mine a latte: coffee shades spill from TikTok into fashion mainstream

A-listers and even royalty help repopularise trend for dressing head to toe in cream, beige and brown

Improve performance

Tips → Humans

Potential Issues

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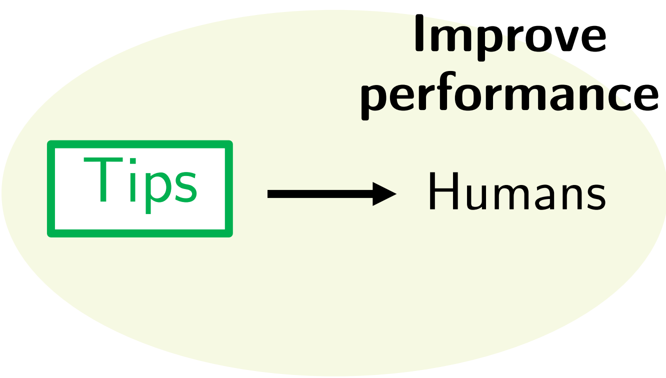
- Private information (e.g., Ibanez et al 2018, Balakrishnan et al 2022, Sun et al 2022)
- Interpretability, inability to precisely implement



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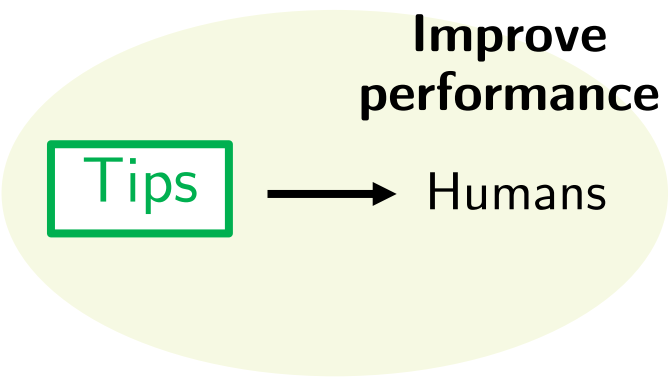
- Learning curve, spillovers



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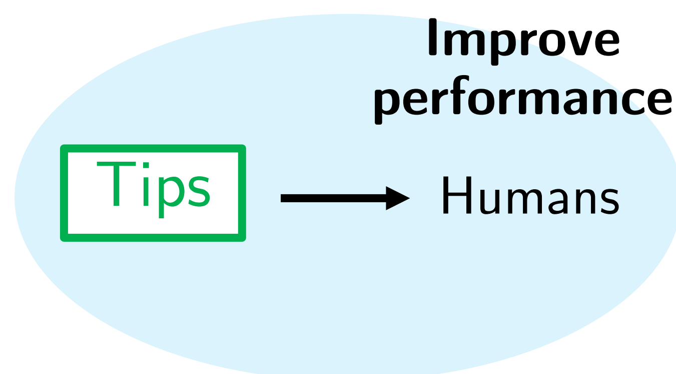
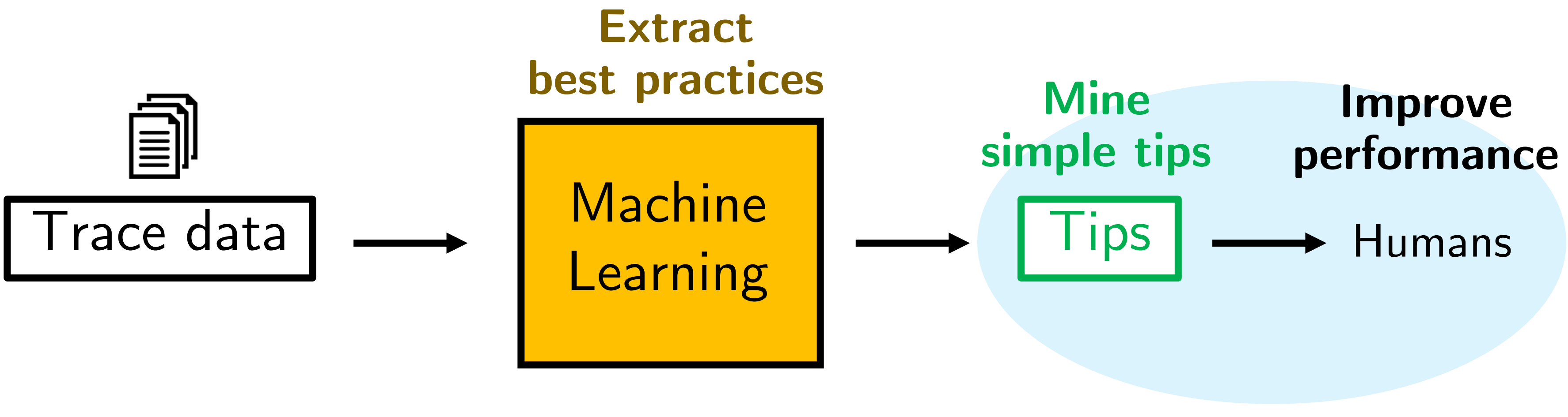
Controlled environment to
observe human learning
& decision-making



How to Help Humans Improve Their Decision-Making?

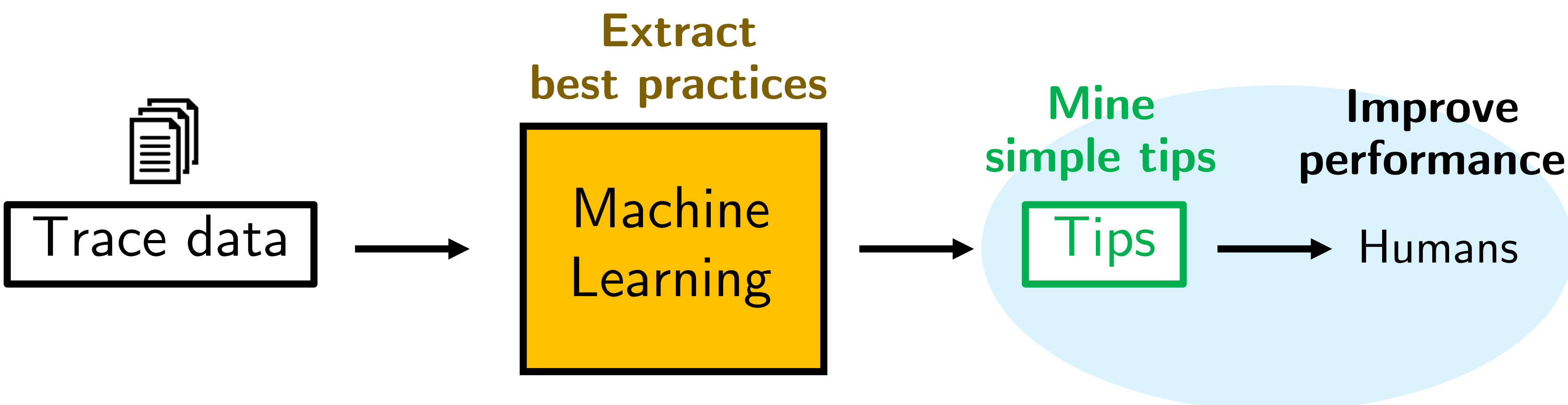


How to Help Humans
Improve Their Decision-Making?

Today:

Experimental Design
Tip Inference
Results: Performance/Compliance
Improving Compliance

with Hamsa Bastani & Osbert Bastani
Major Revision @ Management Science



How to Help Humans
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Experimental Design
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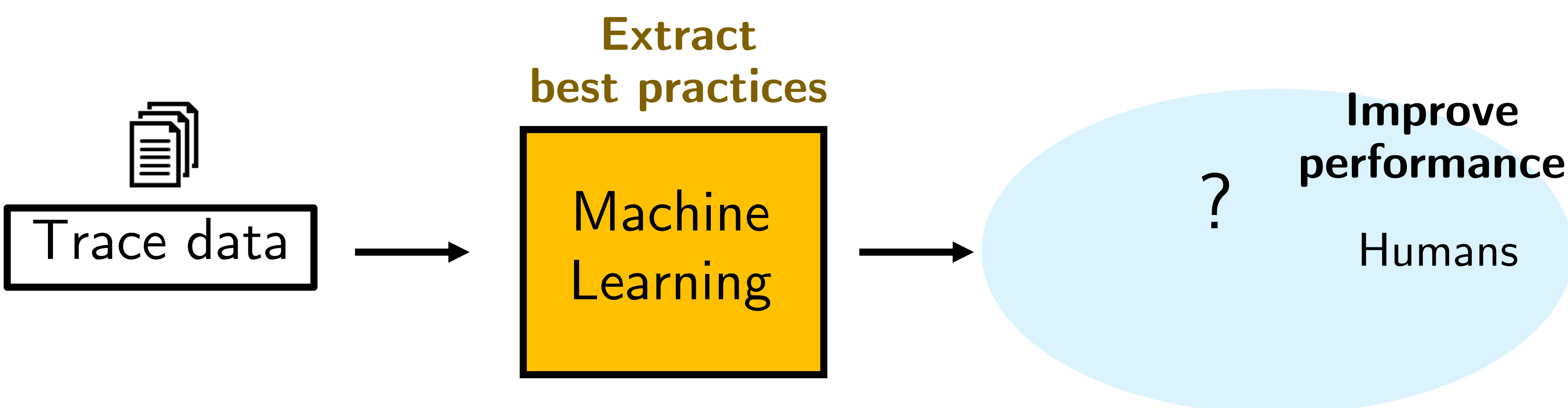
Major Revision @ Management Science

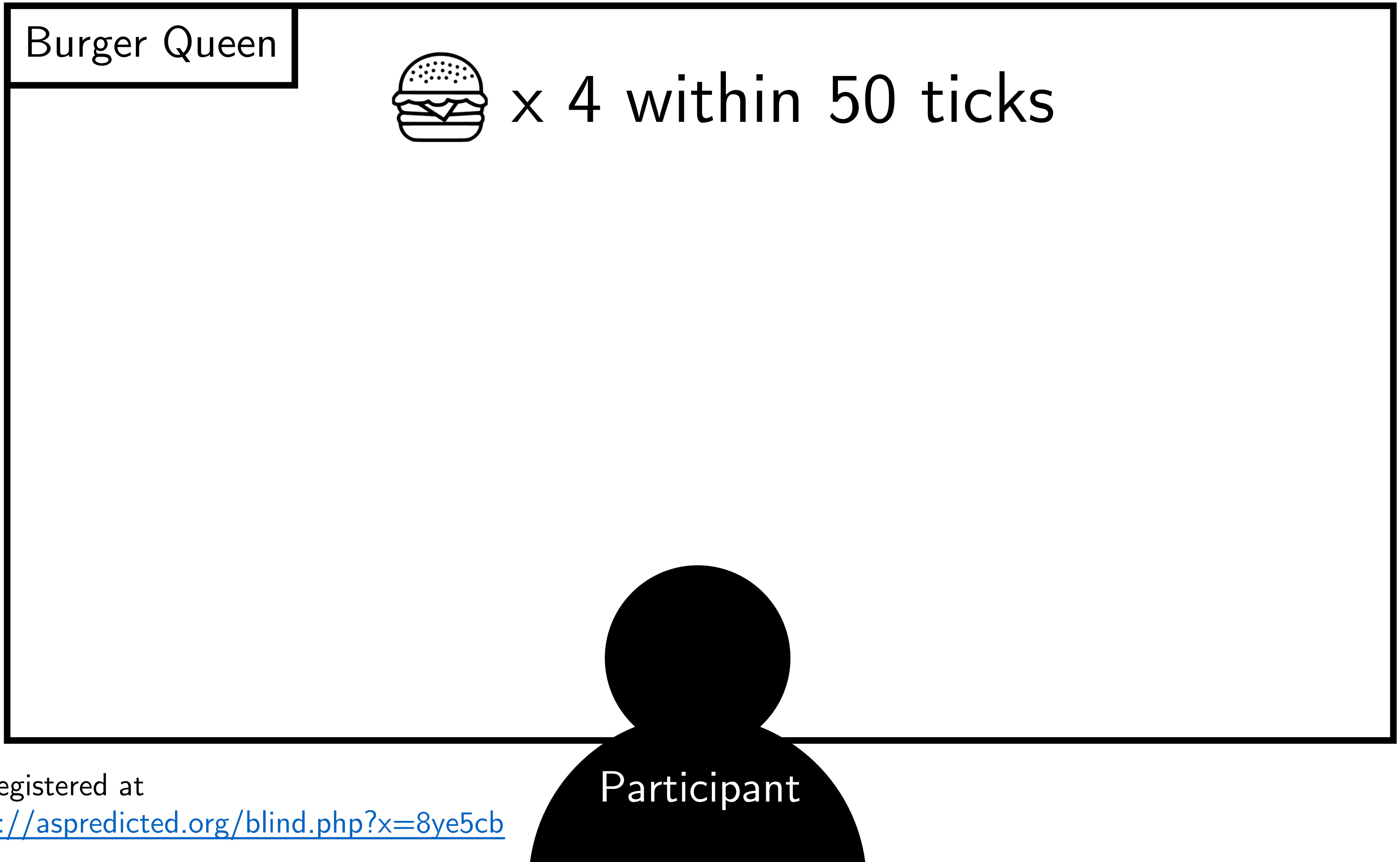
Experimental Design
+ Precision of Tips
+ Learning Post-Tip

with Philippe Blaettchen
Work in Progress



Study 1:

Cooking Game



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

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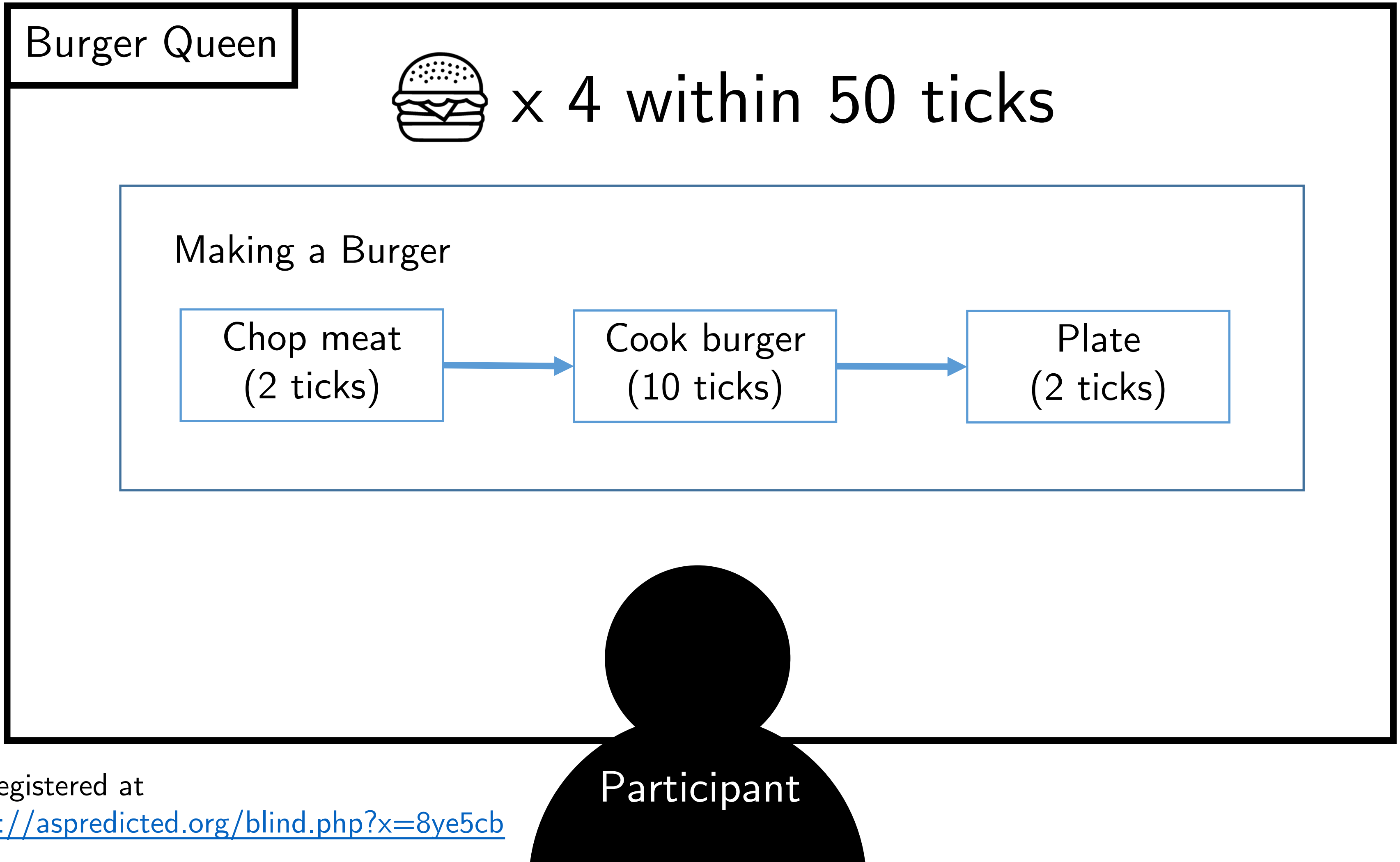

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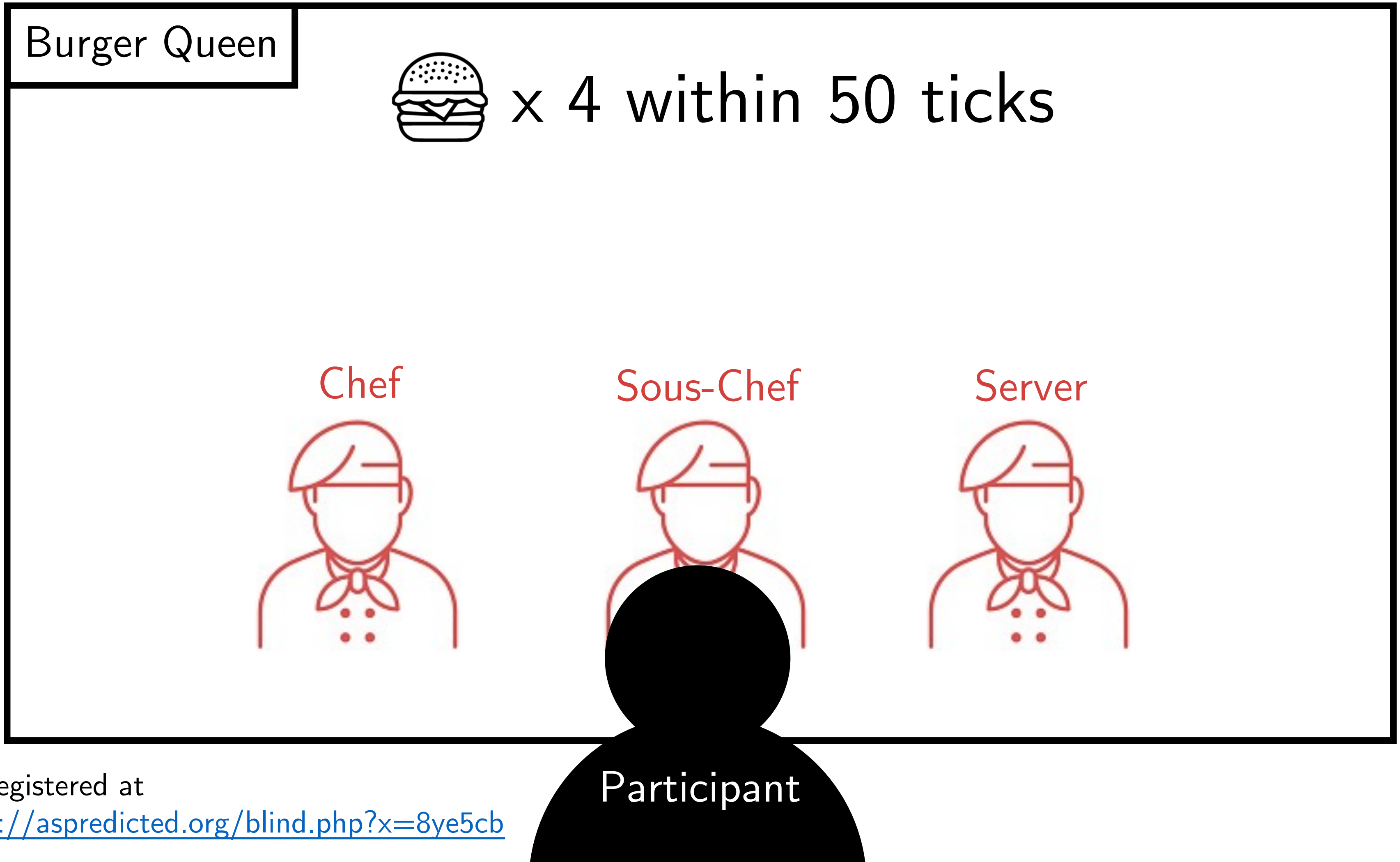

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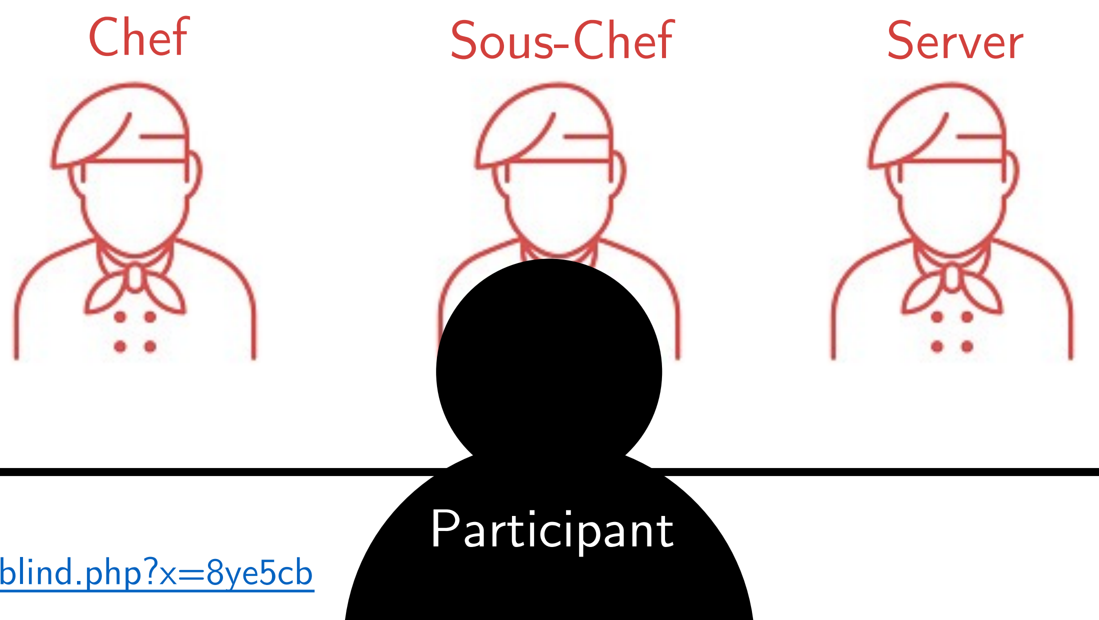
Study 1:

Cooking Game

Burger Queen

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



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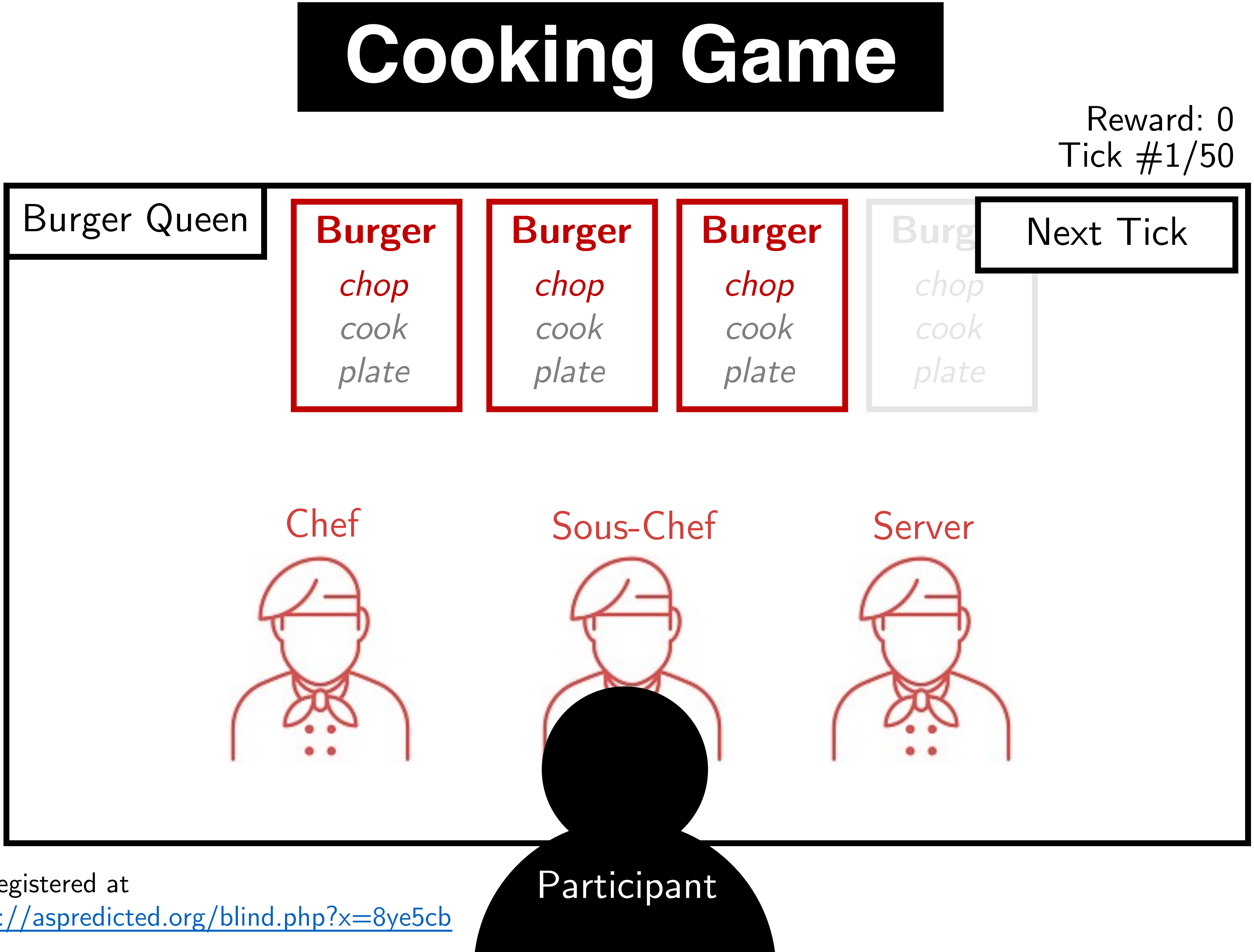

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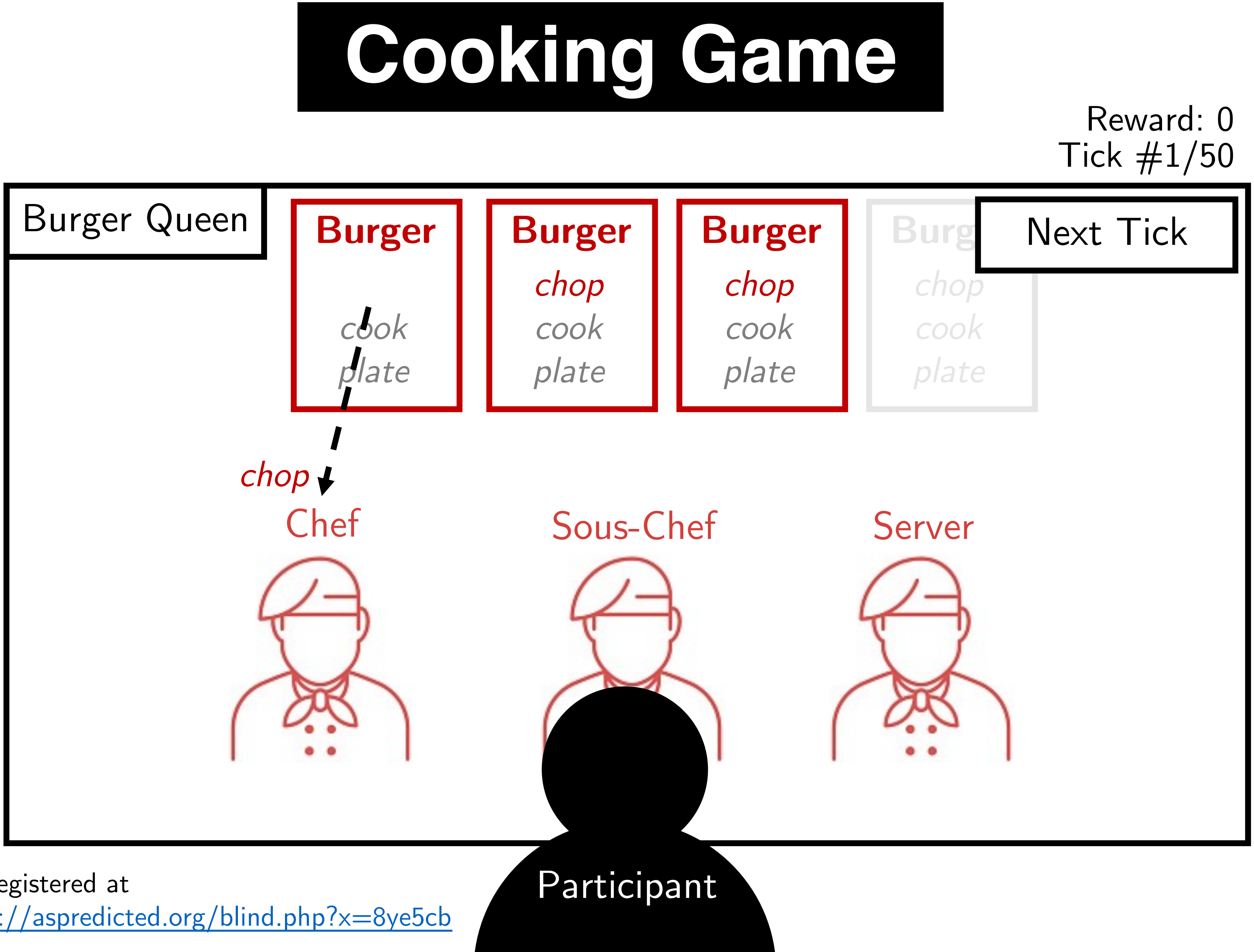

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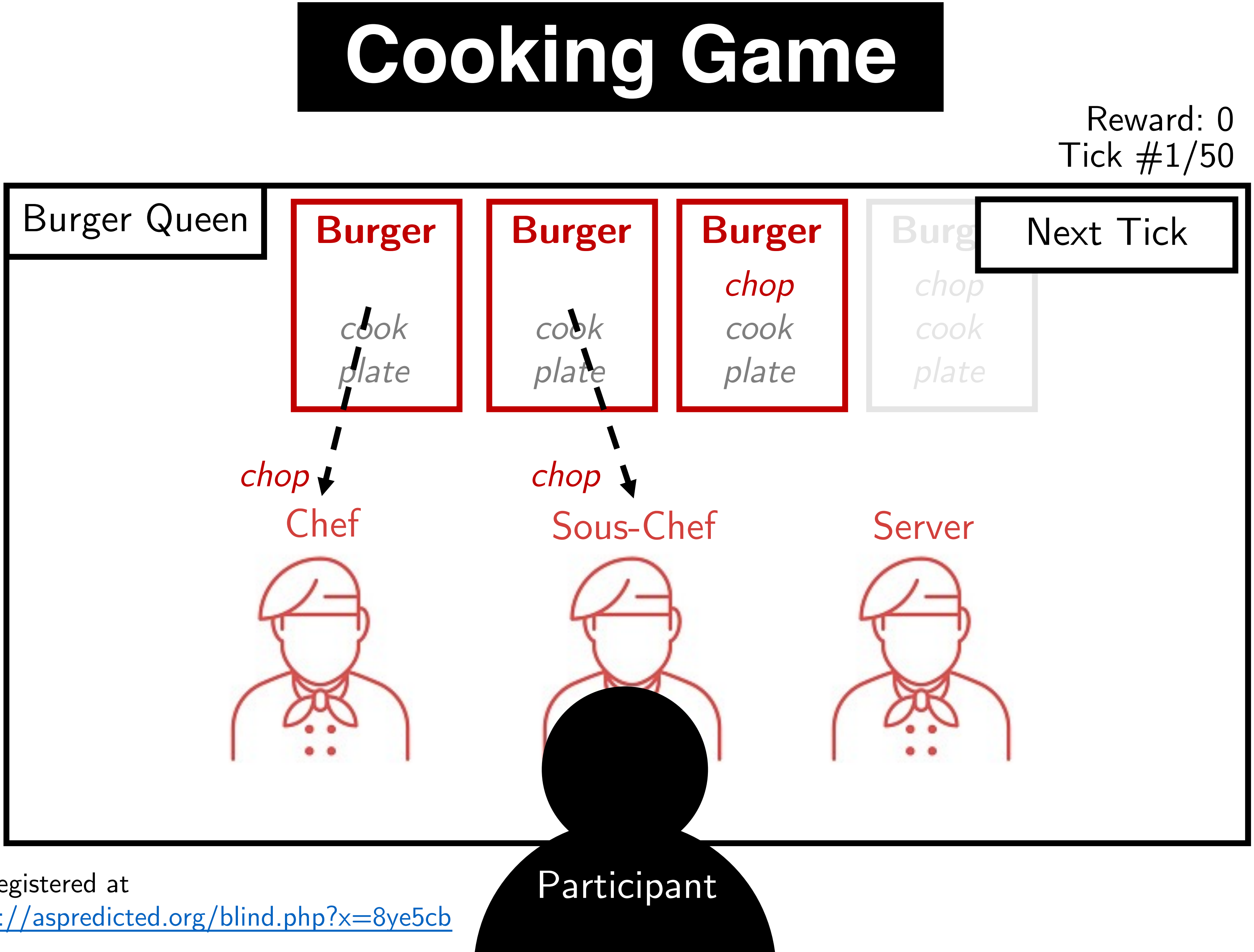

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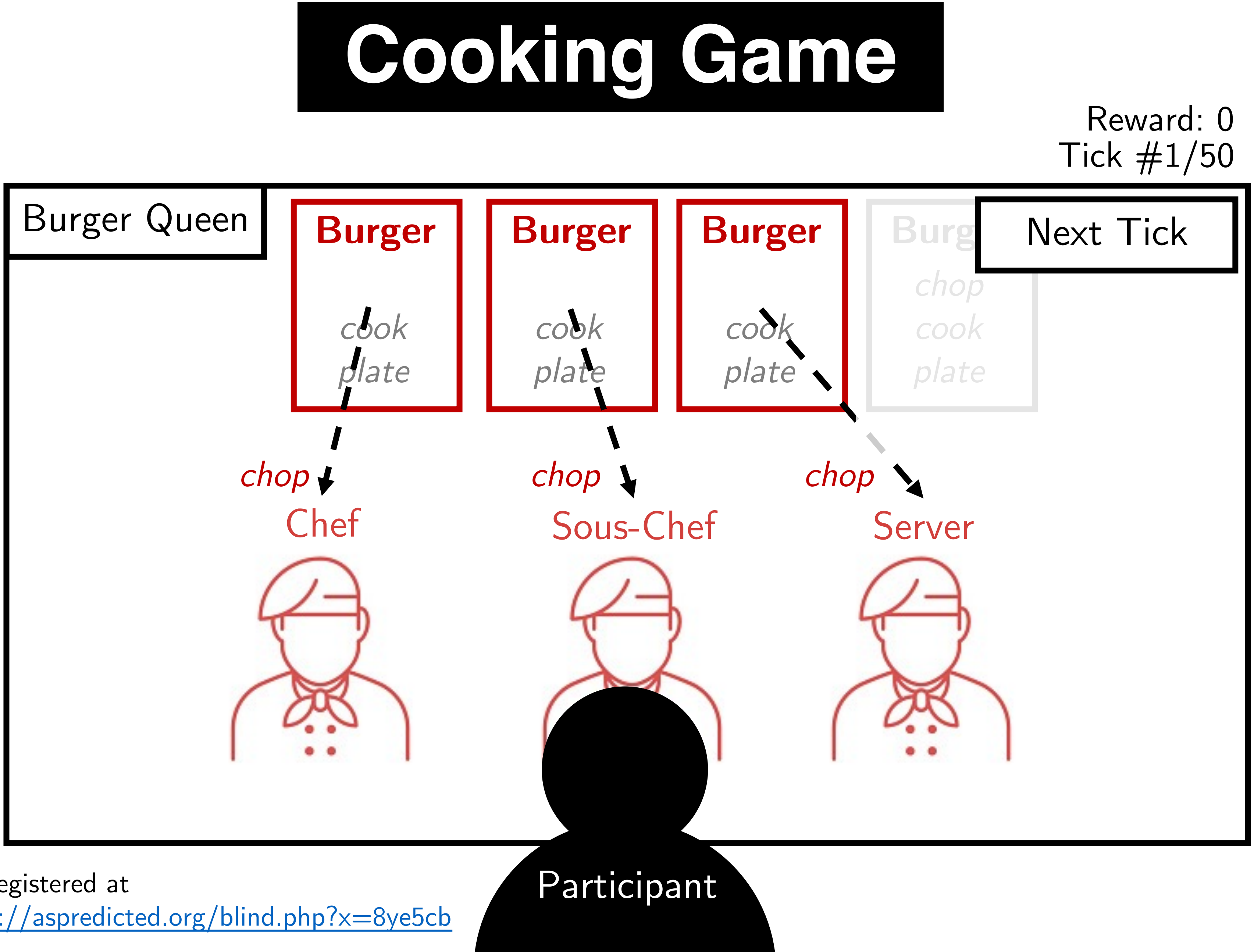

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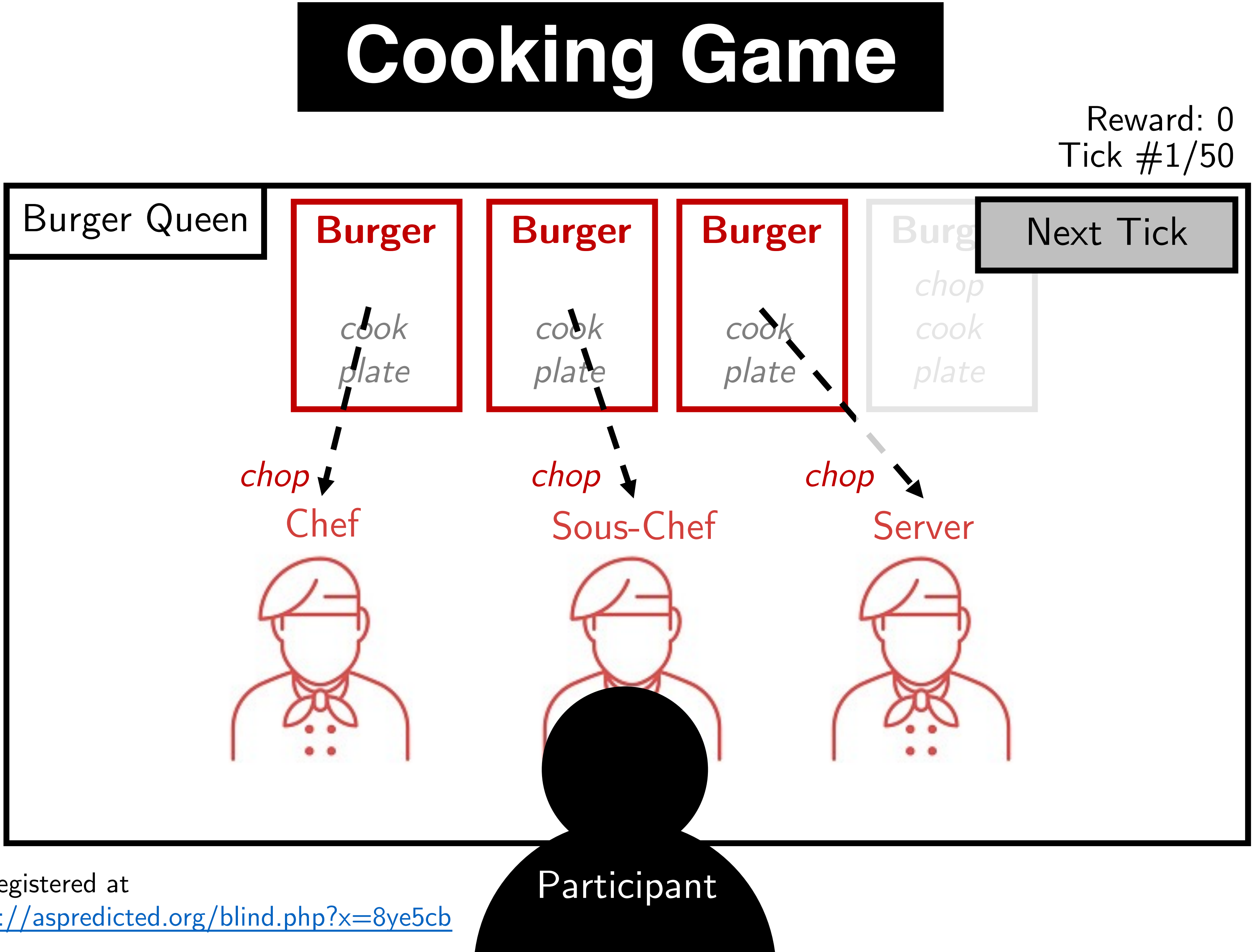

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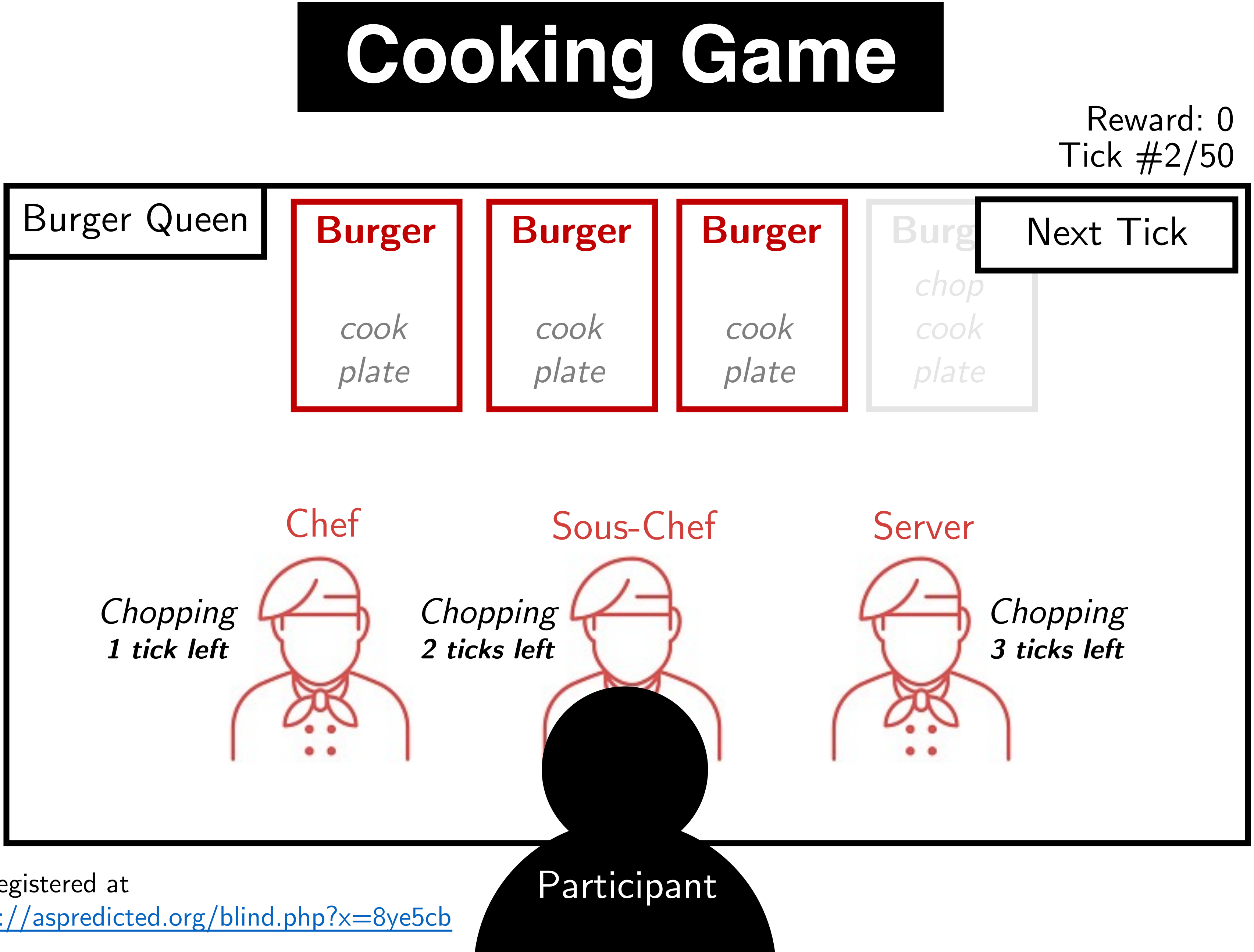

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Study 1:

Design

Disruption Scenario

 x 4 within 50 ticks

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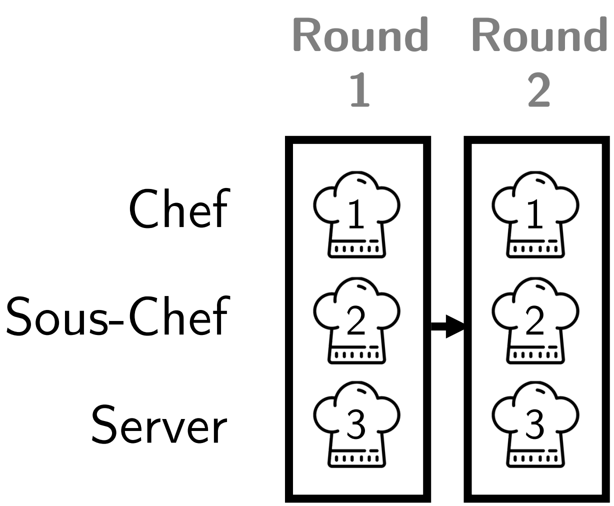

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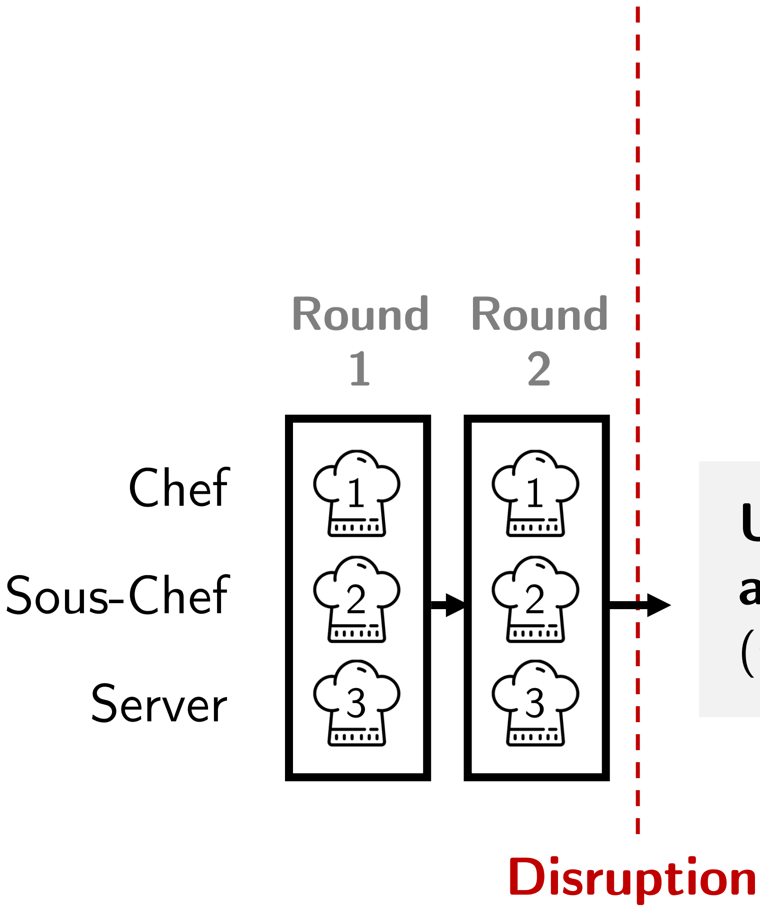

Unfortunately, the Chef is away training for Paris 2024.
(Good luck, Chef!)

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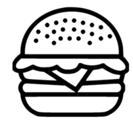
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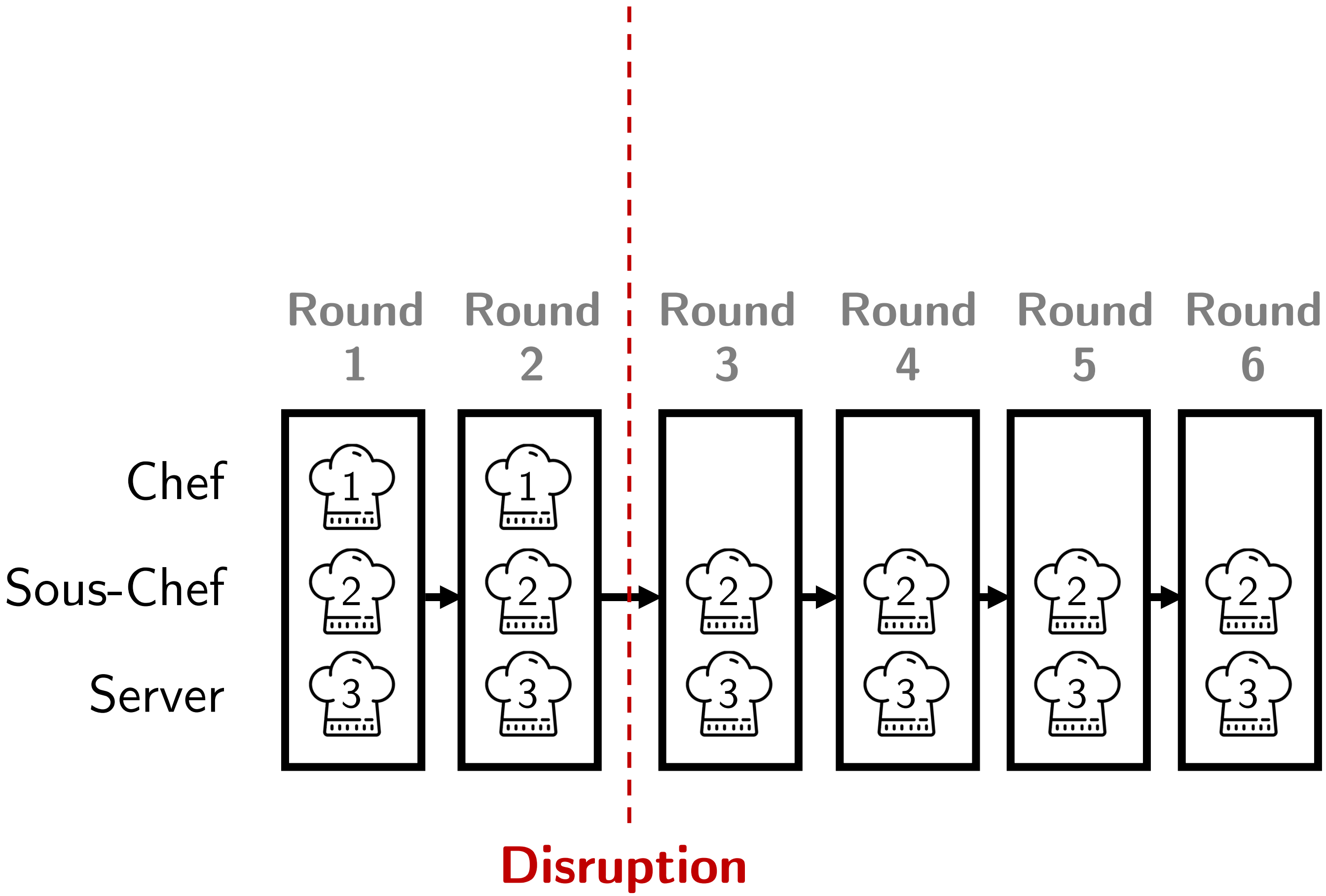

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Problem Formulation

MDP Formulation:

Optimal policy and *human* make sequences of decisions

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

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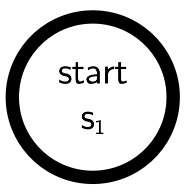
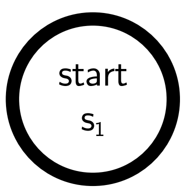
π^*



π



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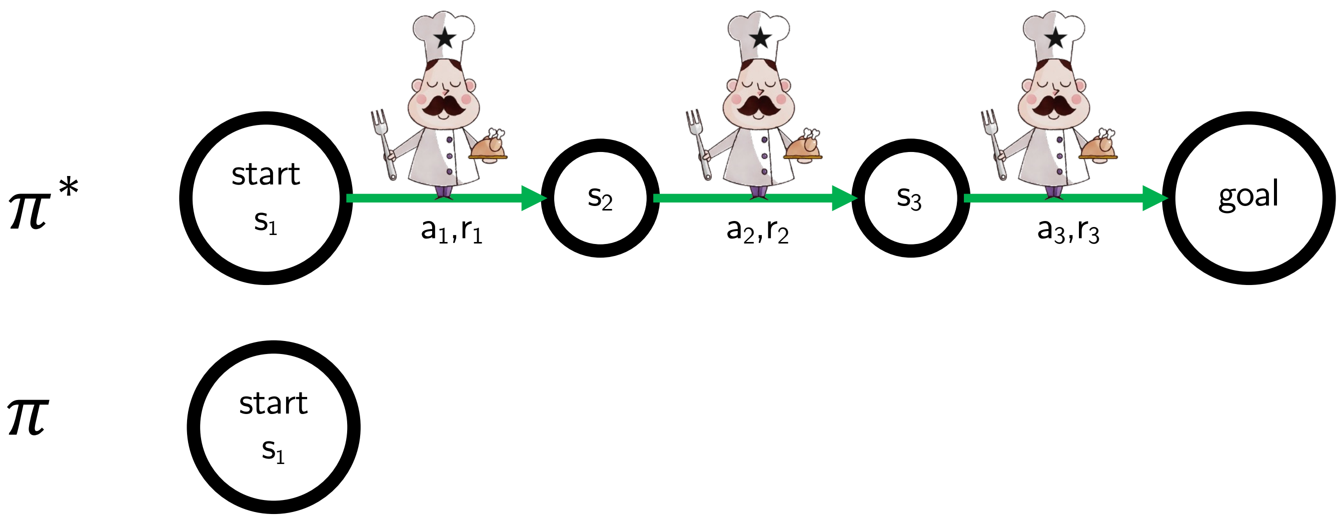

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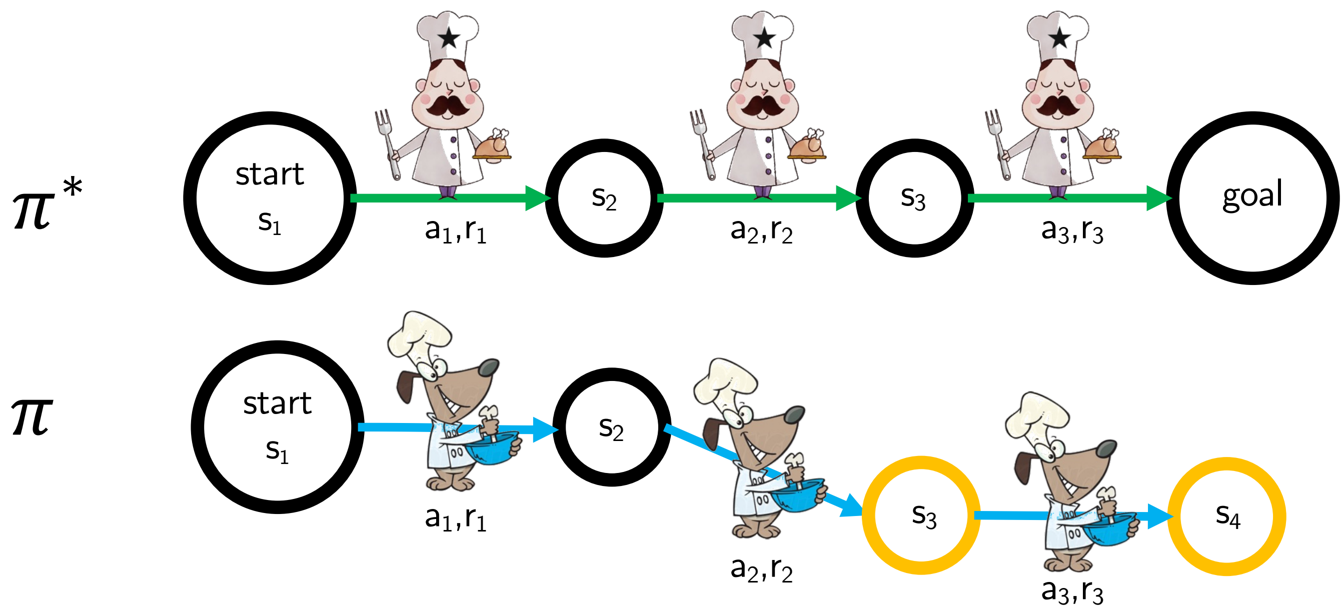
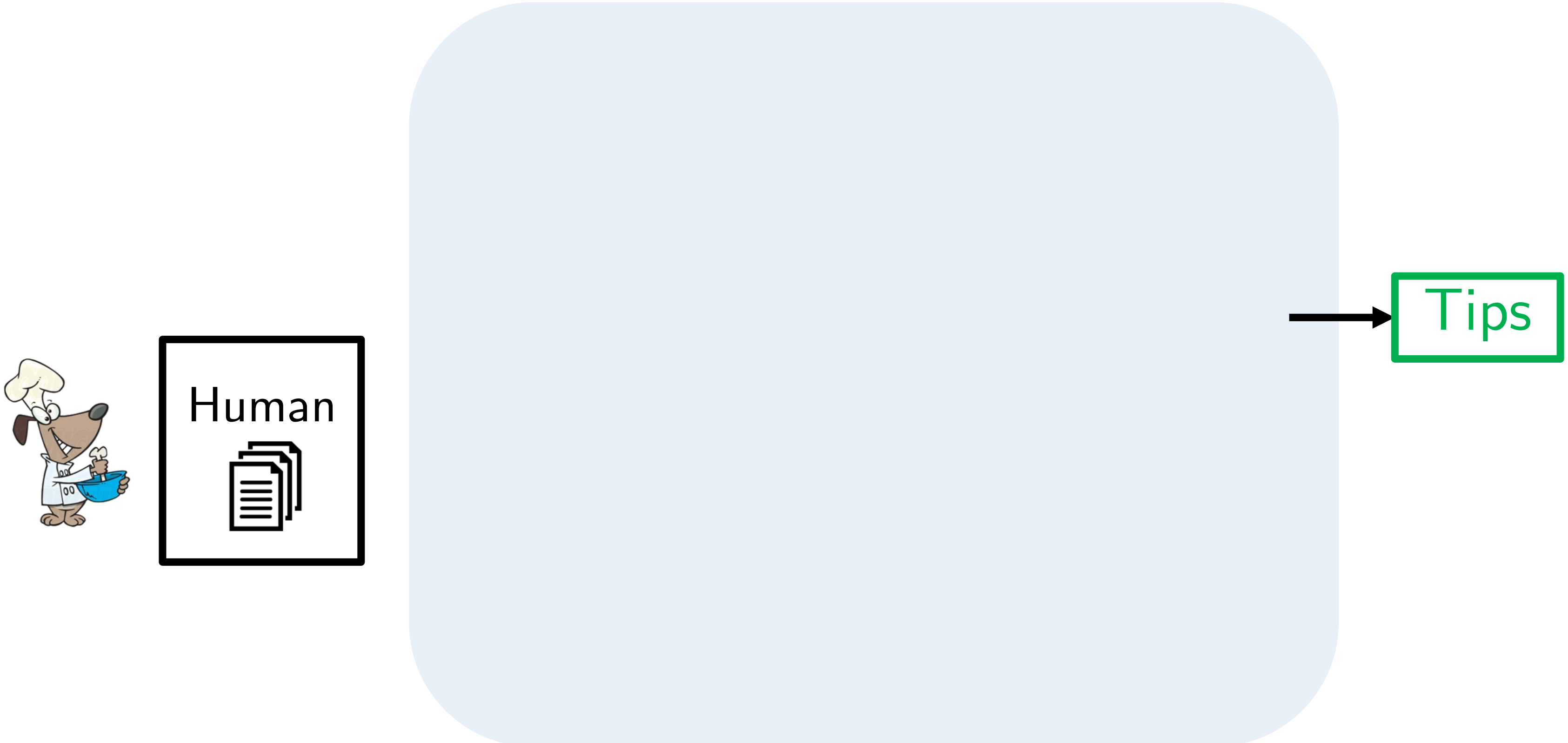


Our Approach



Our Approach

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

Human

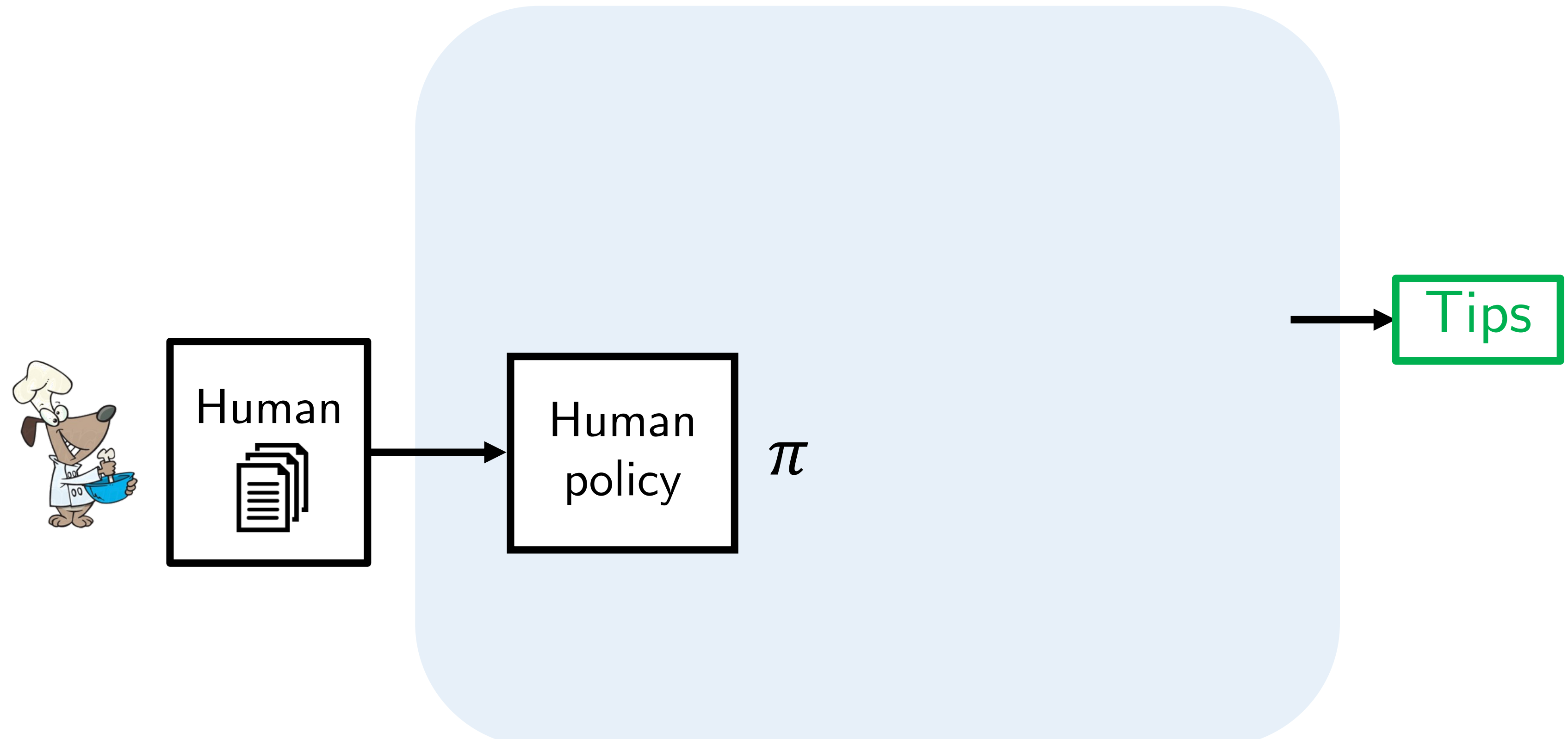
Input:
Trace data $\hat{d}_h$
from human

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

Tips

Our Approach

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

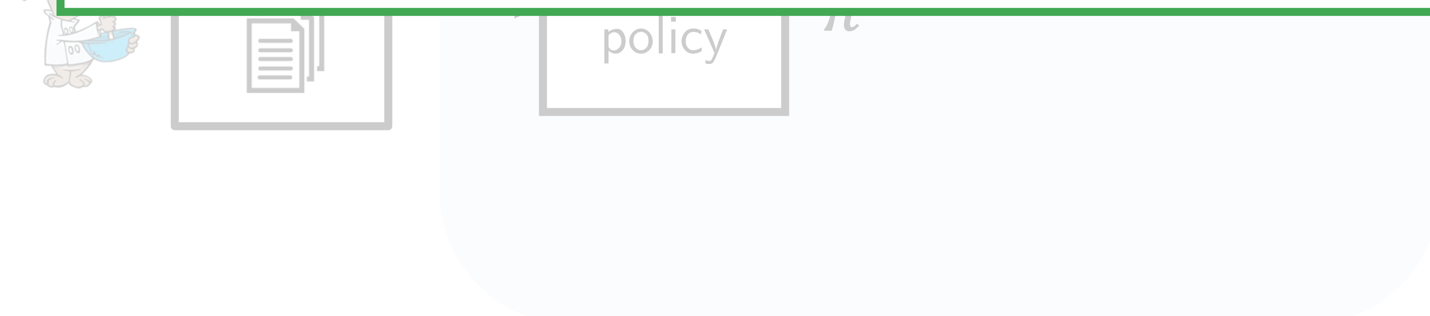


Our Approach

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

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



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

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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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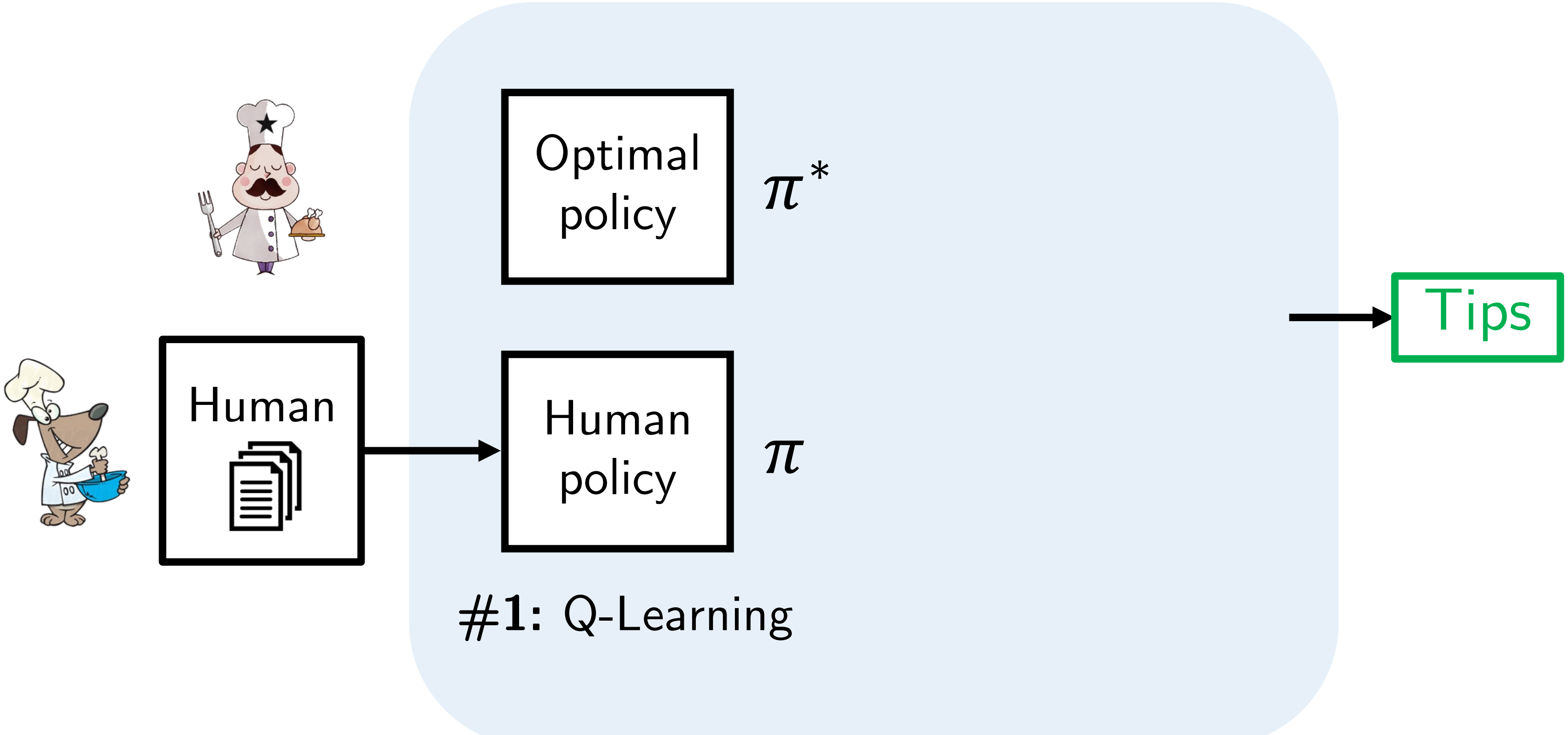

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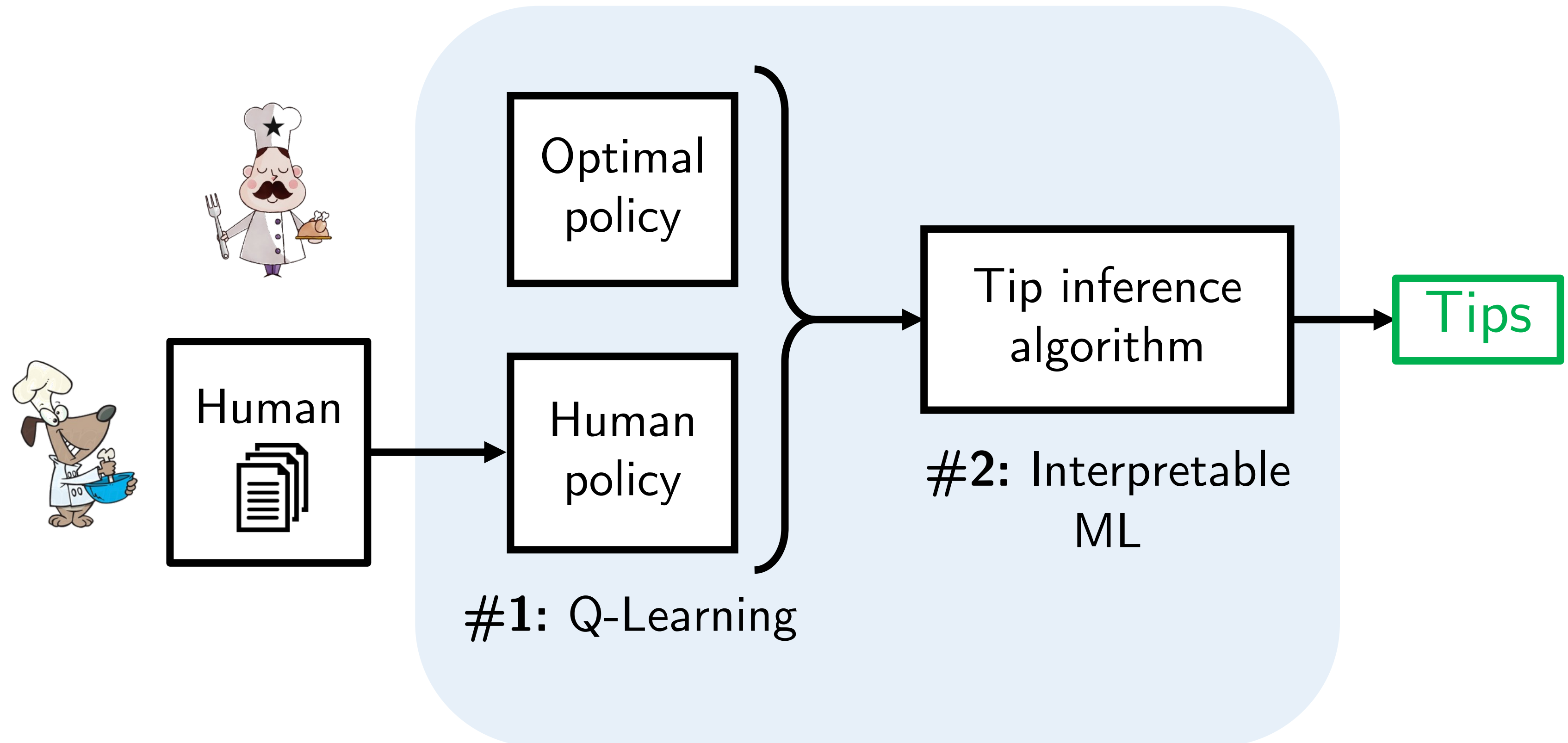

Caruana et al. 2015, Letham et al. 2015

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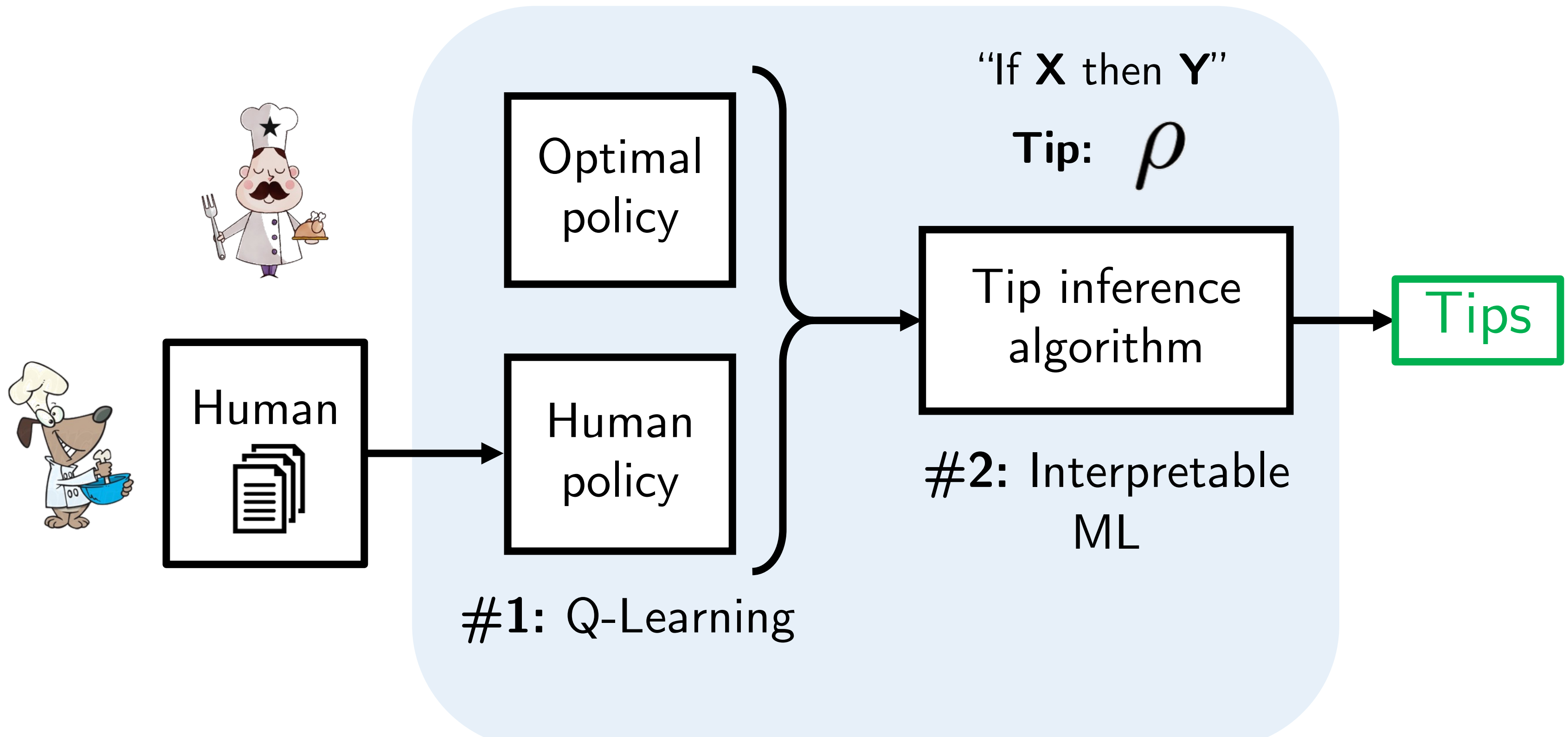

Caruana et al. 2015, Letham et al. 2015

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

- **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.

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

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

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

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

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

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

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

Assign chef to cook the first 2 burgers

Step 2: Tip Inference

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

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

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

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

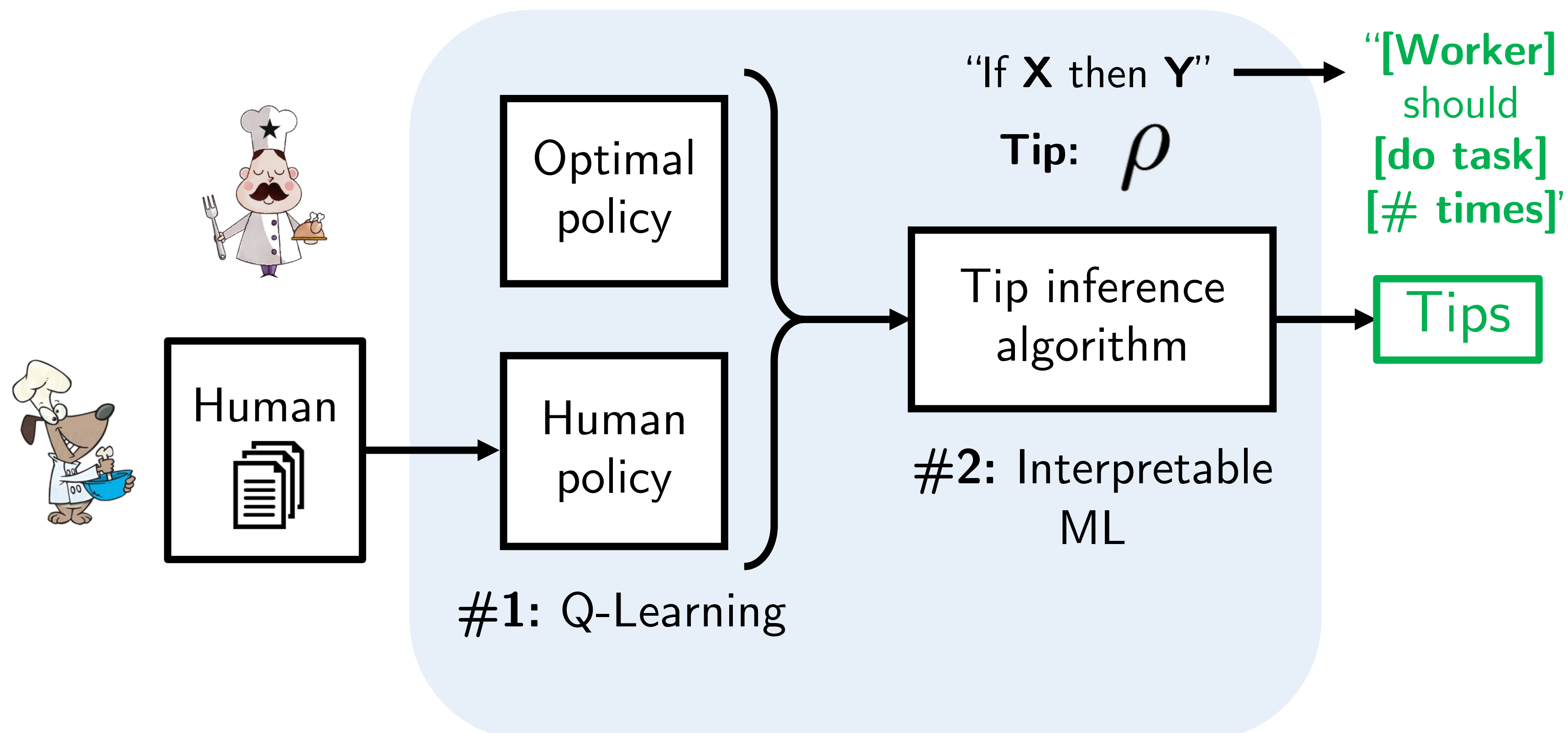
↓

Assign chef to cook the first 2 burgers

↓

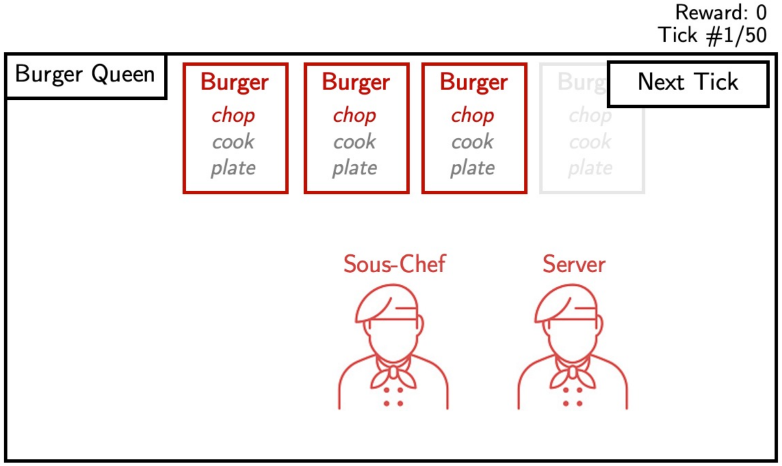
Chef should cook twice

Our Approach



Caruana et al. 2015, Letham et al. 2015

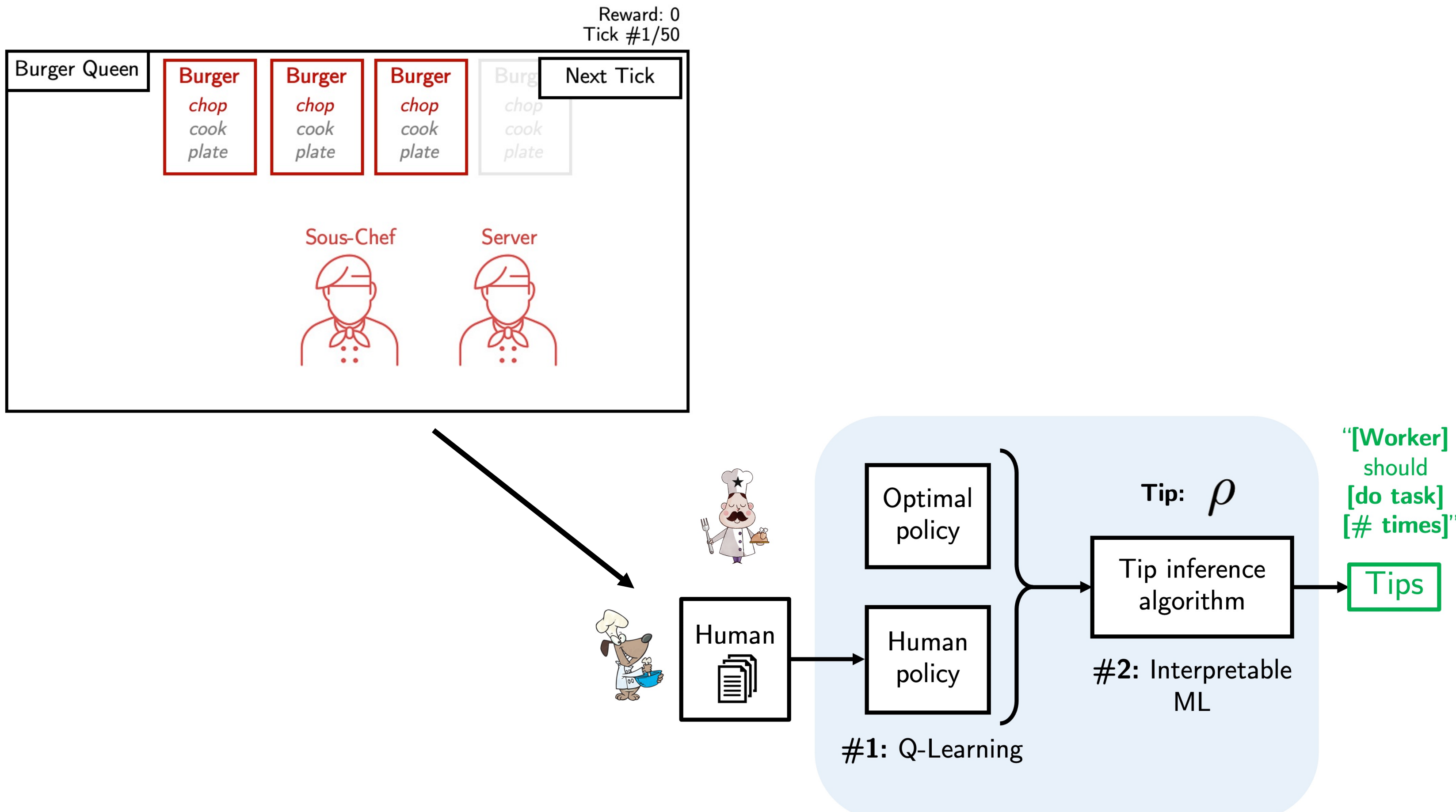
Phase I Collect Trace Data



Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female

Phase I Collect Trace Data



Amazon Mechanical Turk, N = 172

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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

Server
should cook twice

Human

Most frequent tip
chosen by participants

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

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

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

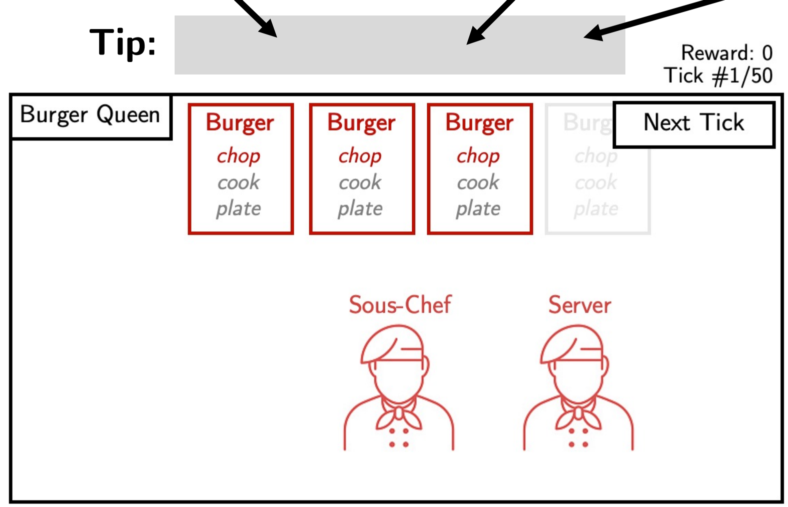
Control	Algorithm	Human	Baseline
- No tip -	Server should cook twice	Server should cook once	Sous-Chef should plate twice

Phase II

Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

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



Phase II

Amazon Mechanical Turk, N = 1,011

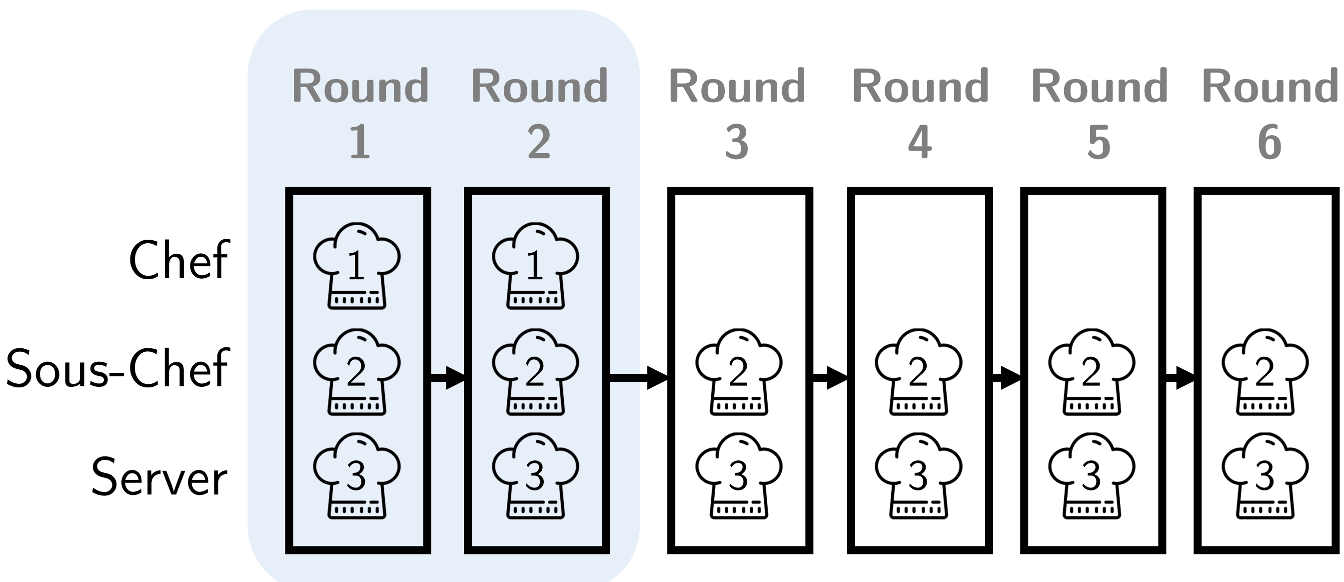
mean age 34.9, 60% female

Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once

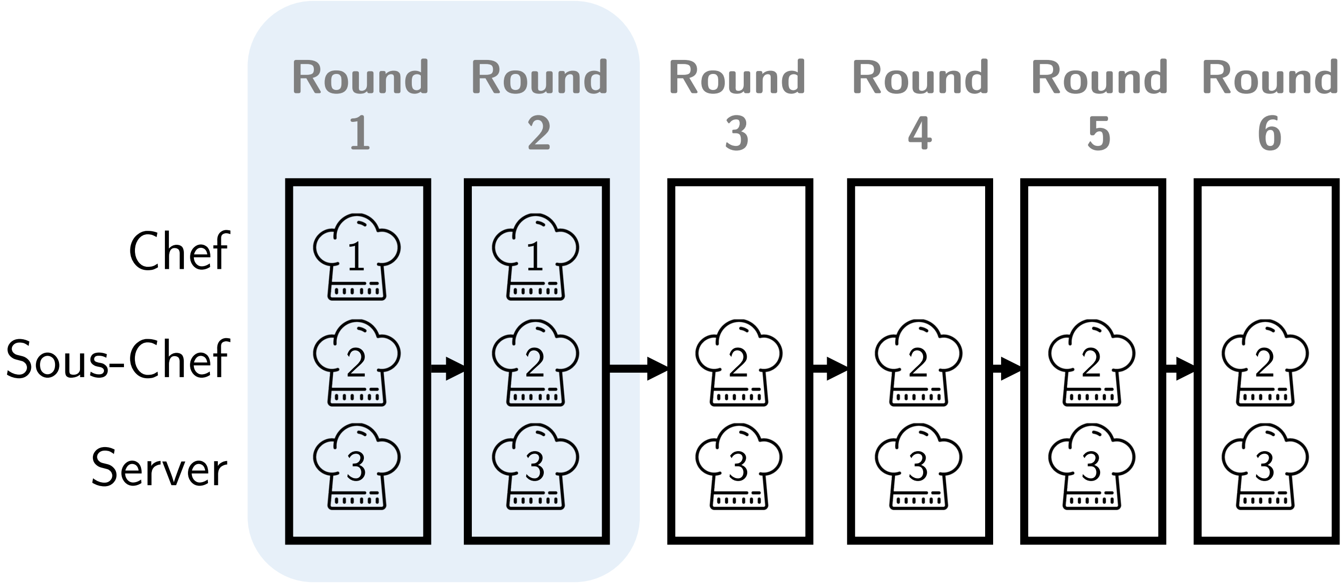
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



Algorithm vs Human

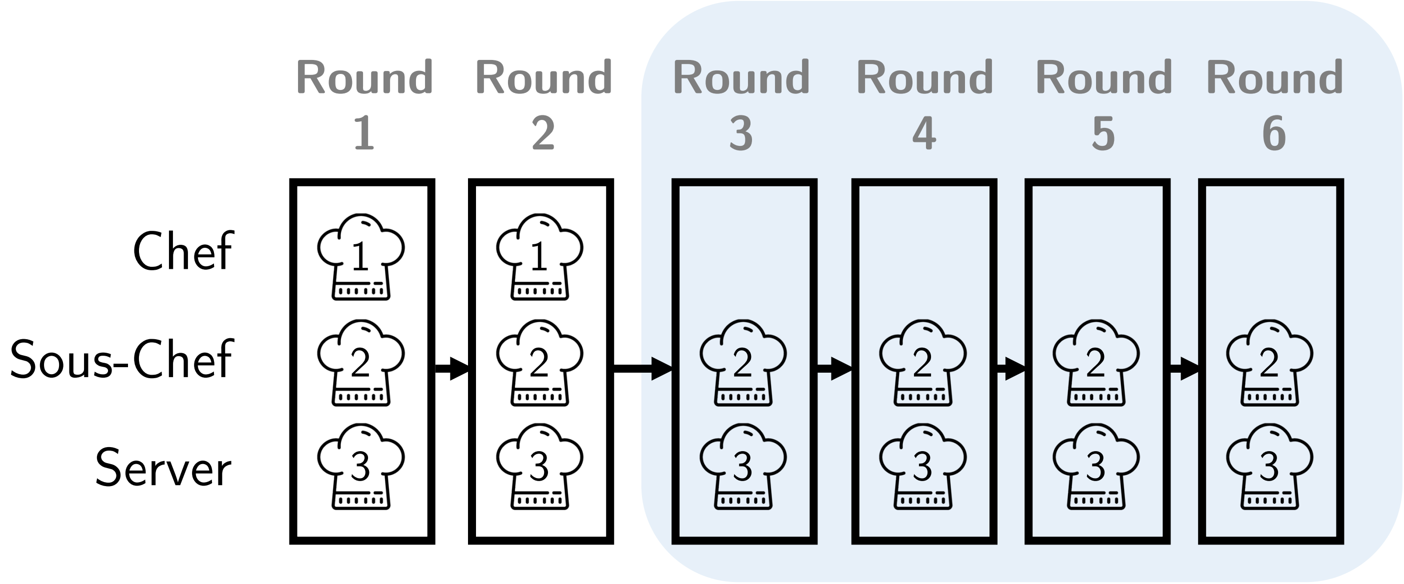
Algorithm	Human
Server should cook twice	Server should cook once



"Server shouldn't cook"

Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



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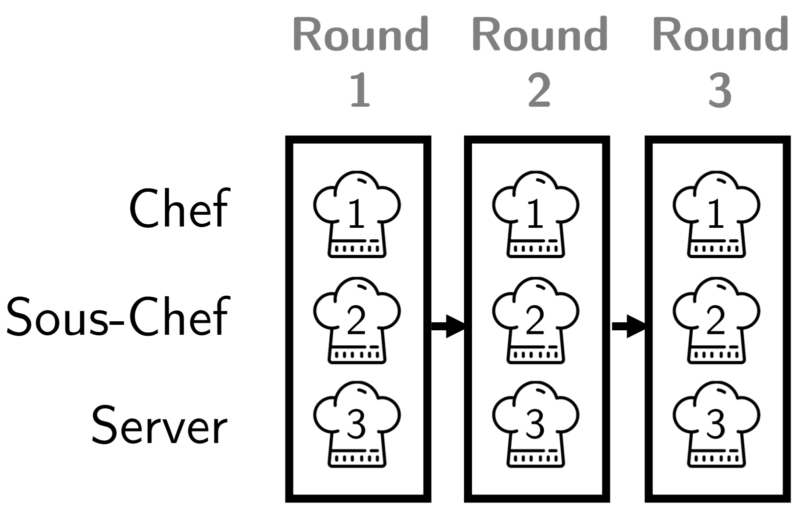
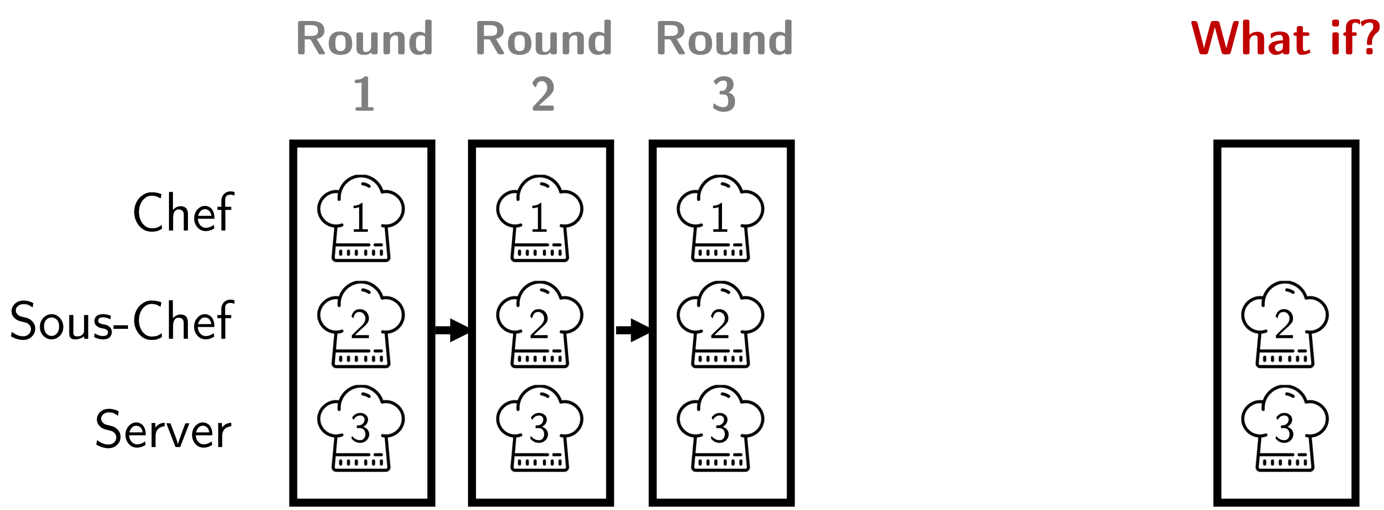


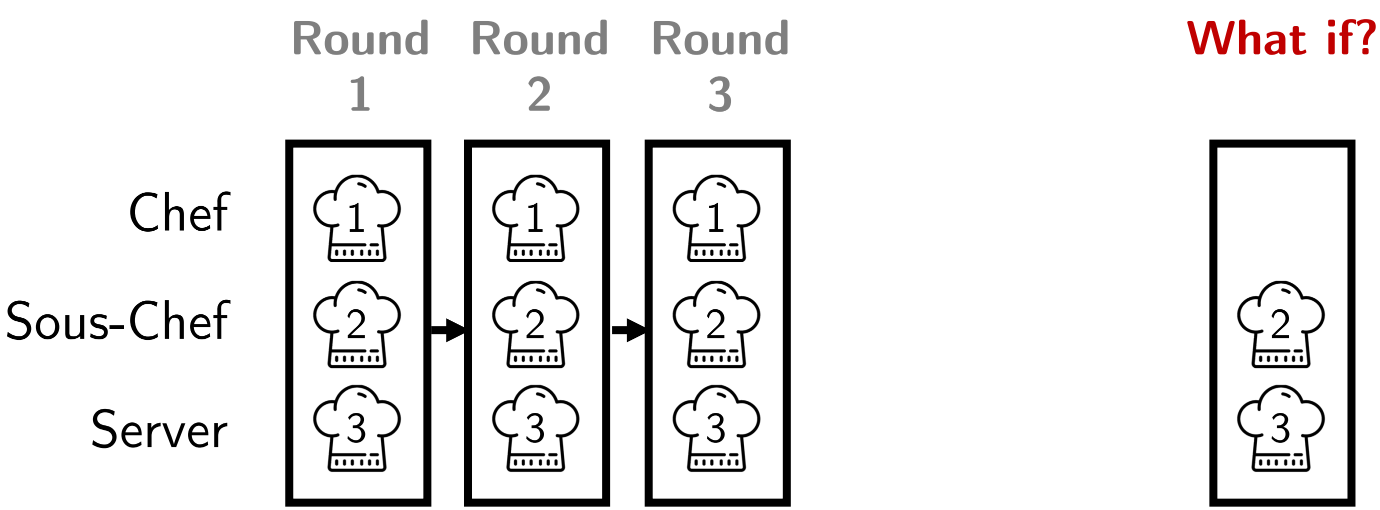
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once



Algorithm vs Human

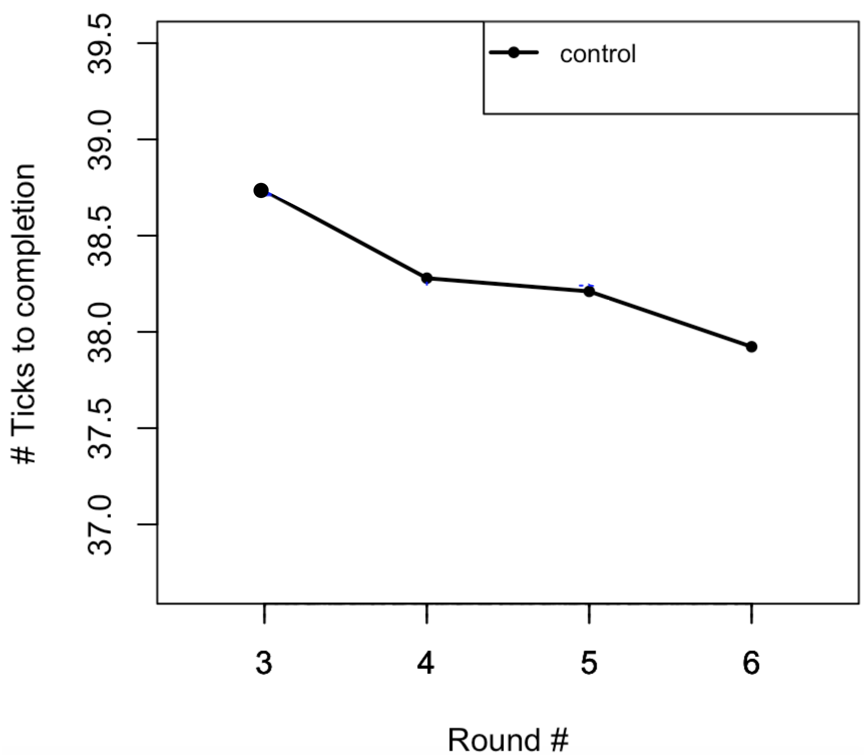
Algorithm	Human	Hypothetical
Server should cook twice	Server should cook once	Server shouldn't cook



Study 1:

Results People Improve Over Time

Ticks to completion



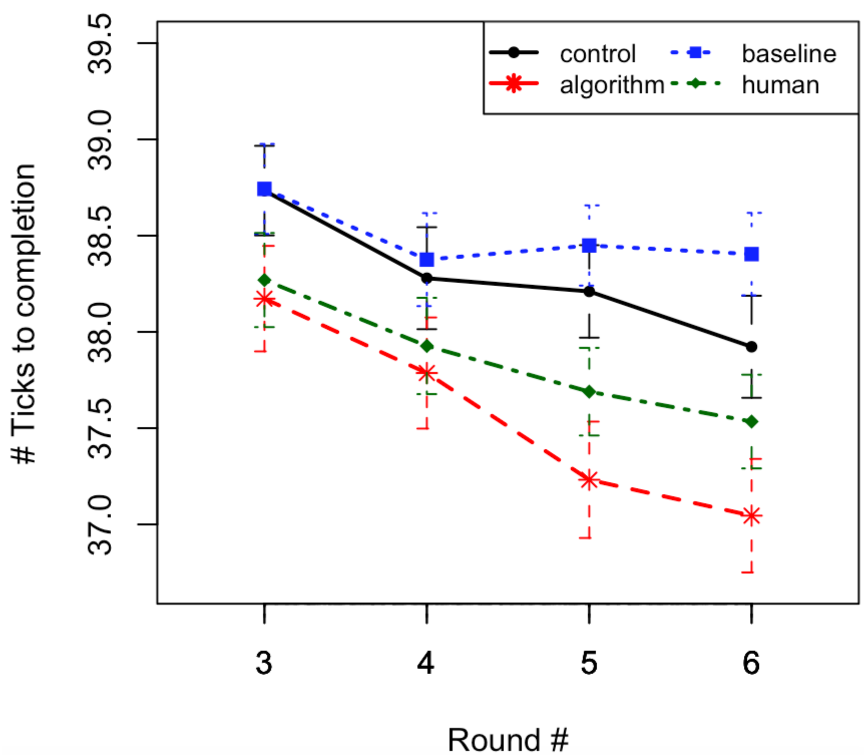
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Results Our Tip Improves Performance

Ticks to completion



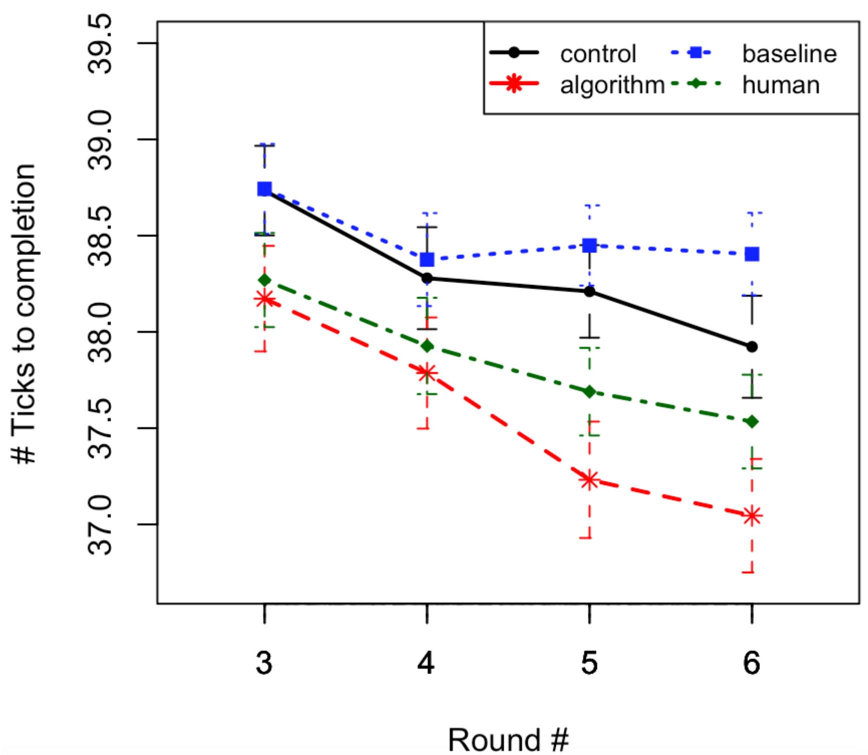
One-sided T-Tests

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

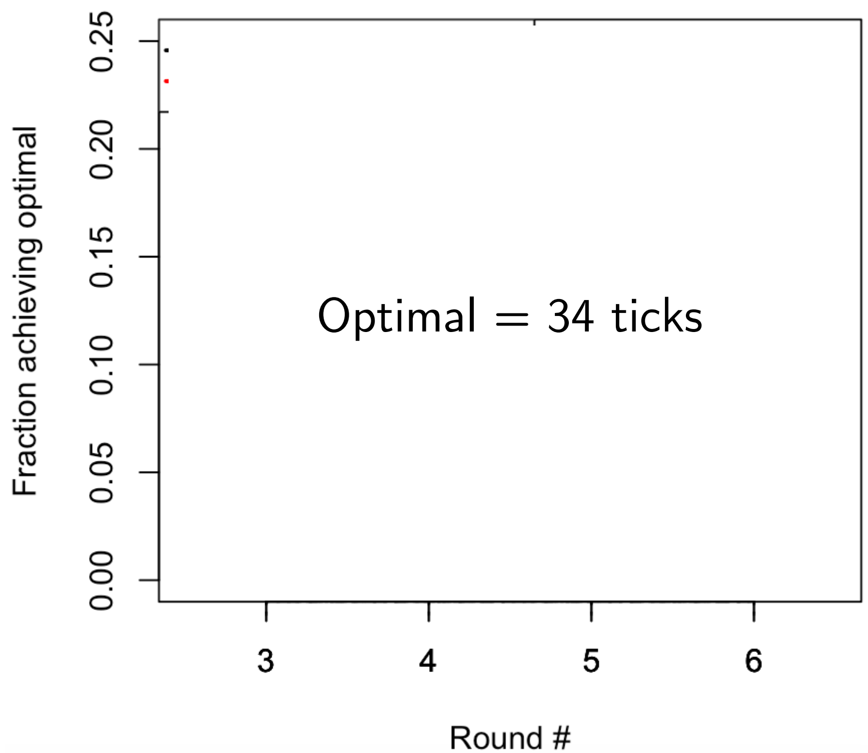
Amazon Mechanical Turk, $N = 1{,}011$
mean age 34.9, 60% female

Study 1:
Results

Ticks to completion



Fraction achieving optimal



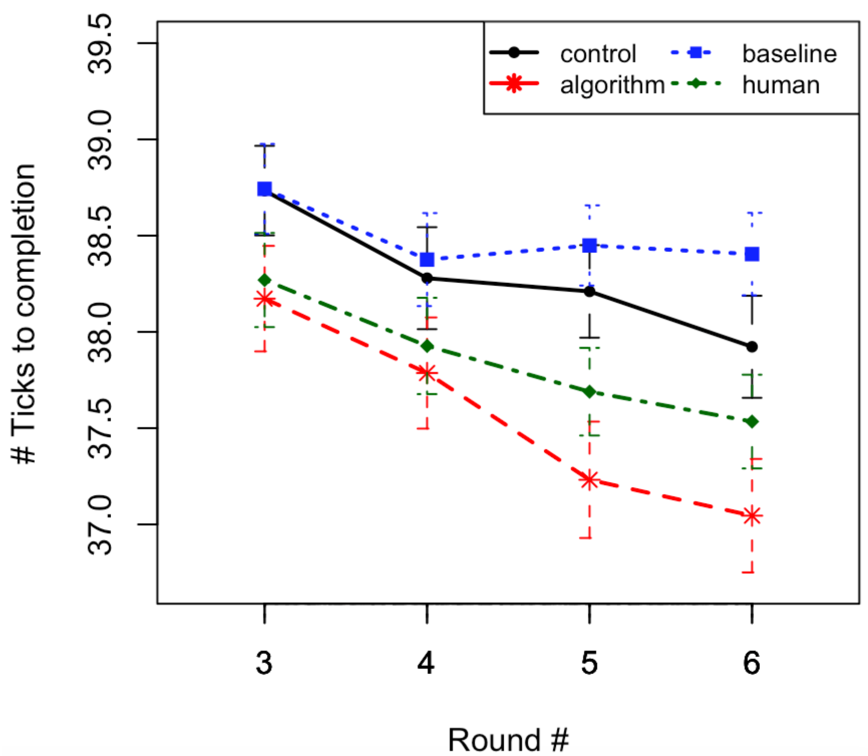
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

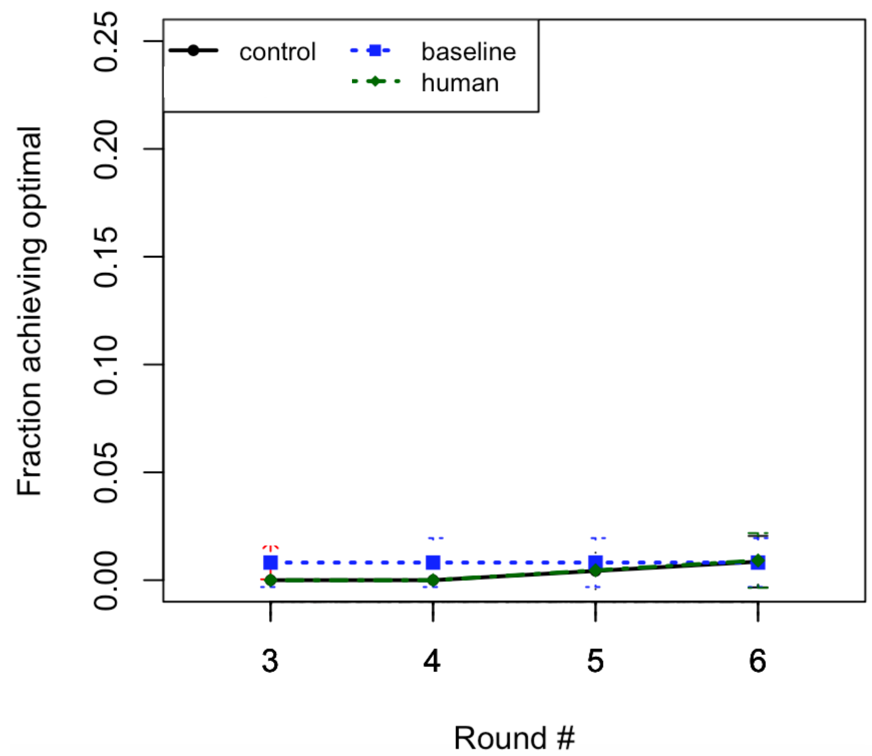
Study 1:

Results Difficult to Reach Optimal

Ticks to completion



Fraction achieving optimal



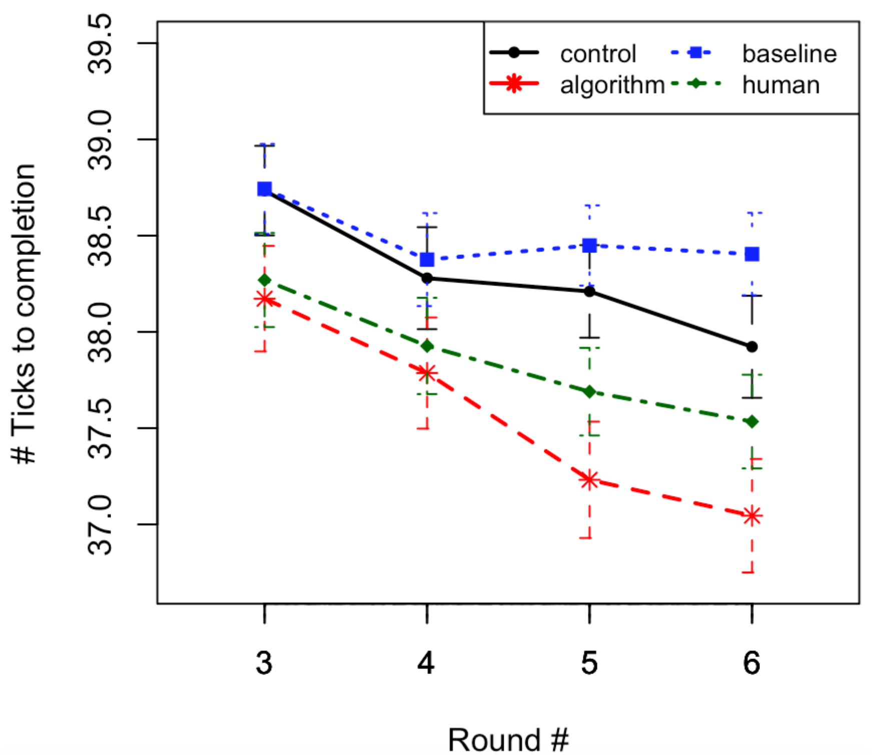
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

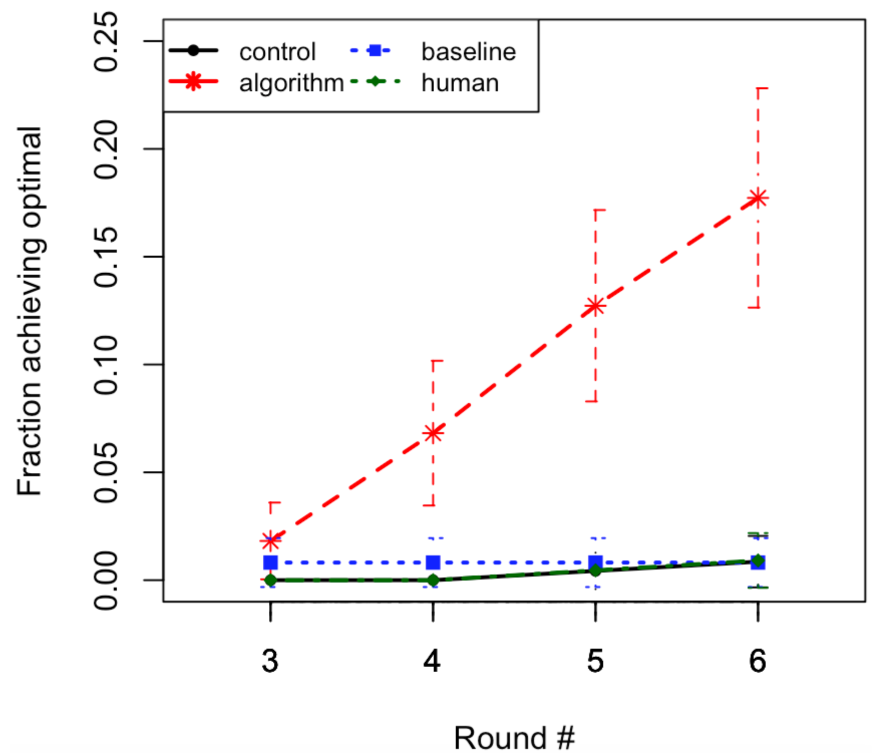
Study 1:

Results Our Tip Helps Reach Optimal

Ticks to completion



Fraction achieving optimal

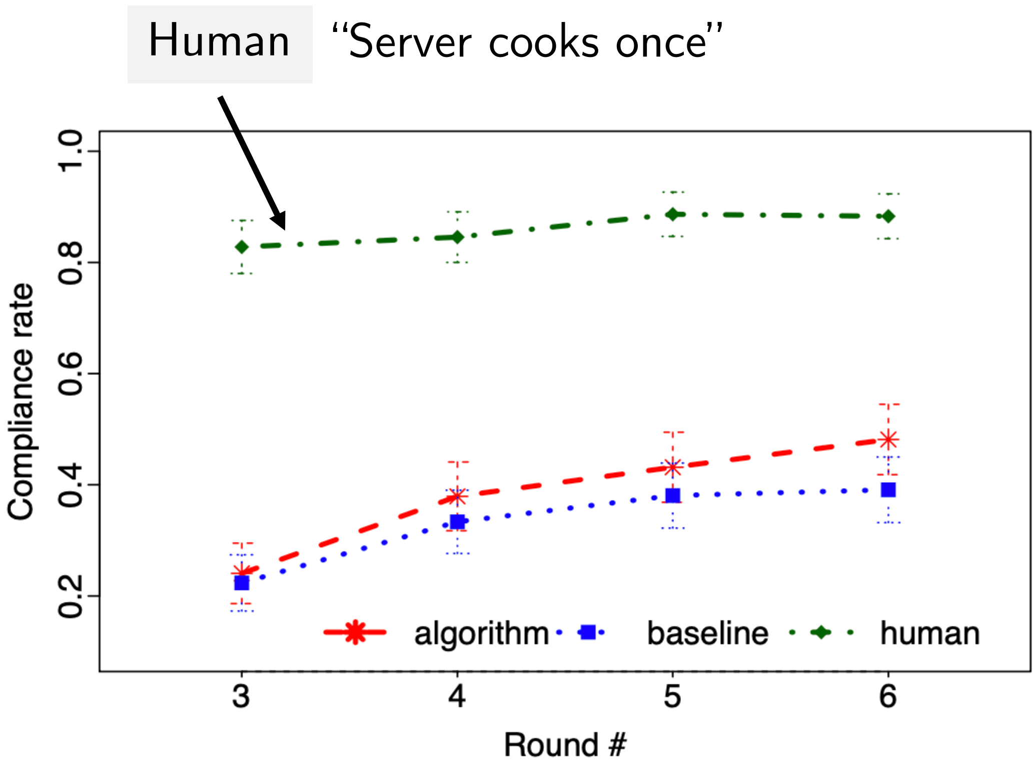


Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Study 1:

Results Complying with Intuitive Tip



Amazon Mechanical Turk, N = 1,011

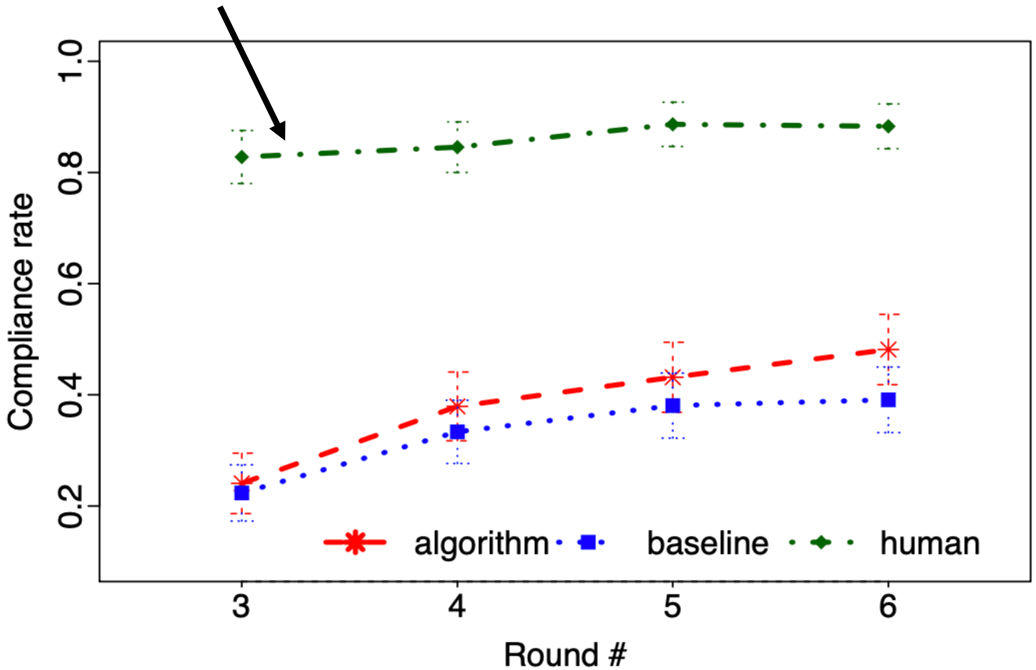
mean age 34.9, 60% female

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

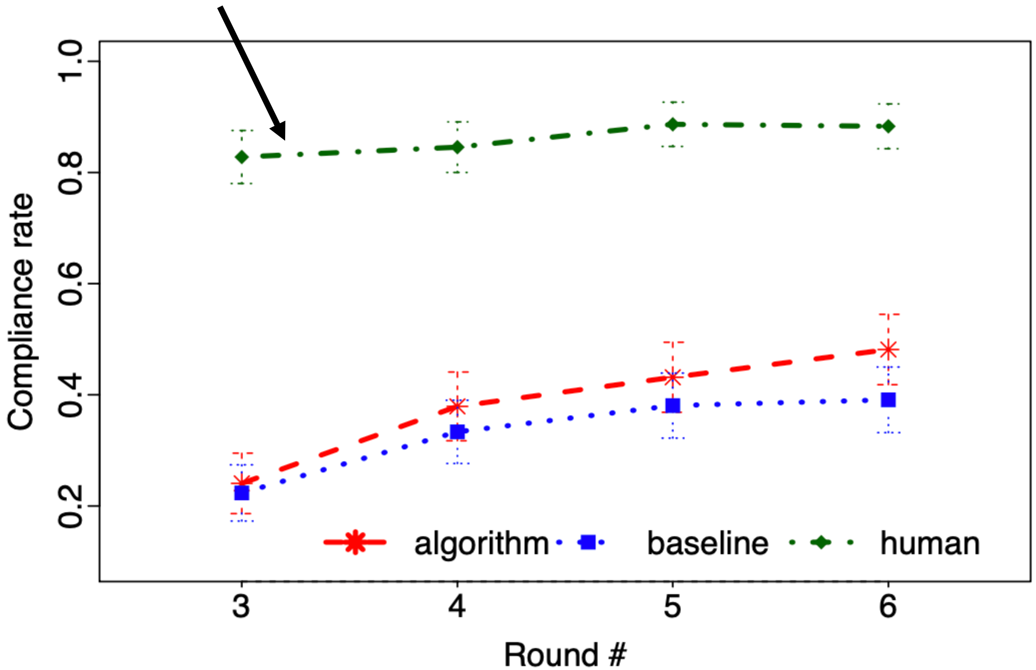
mean age 34.9, 60% female

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

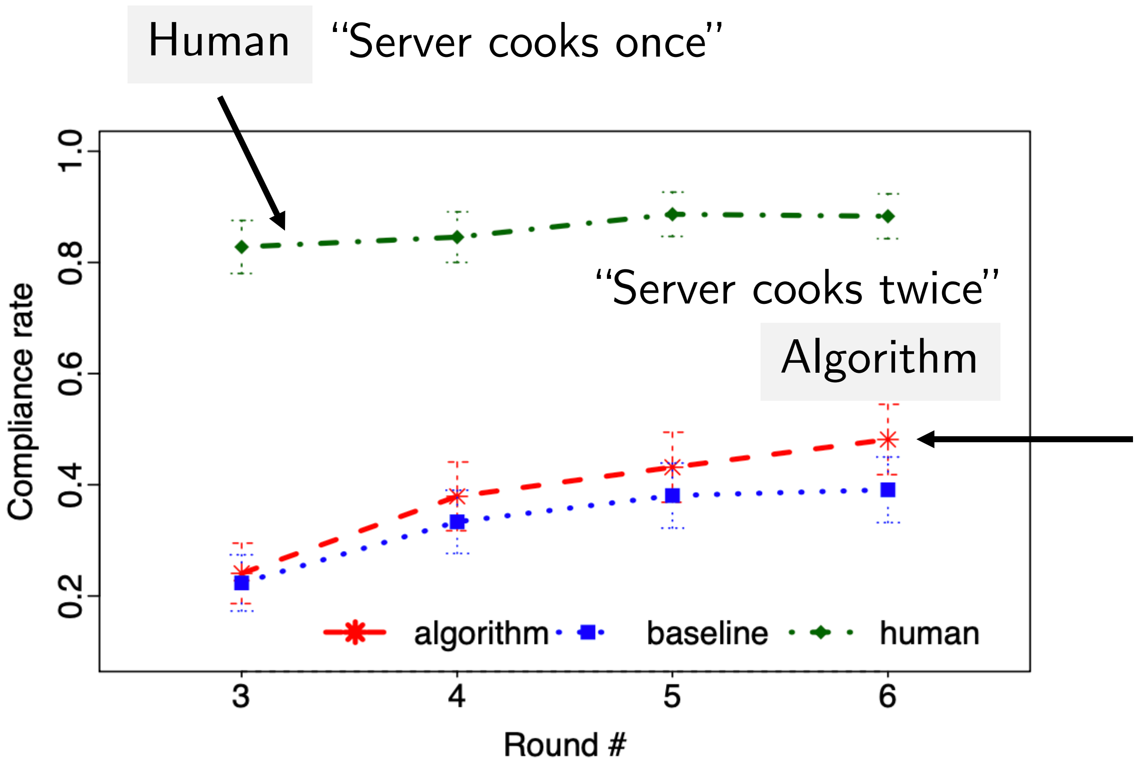
“It stunk honestly. **The server takes forever to cook.”**

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

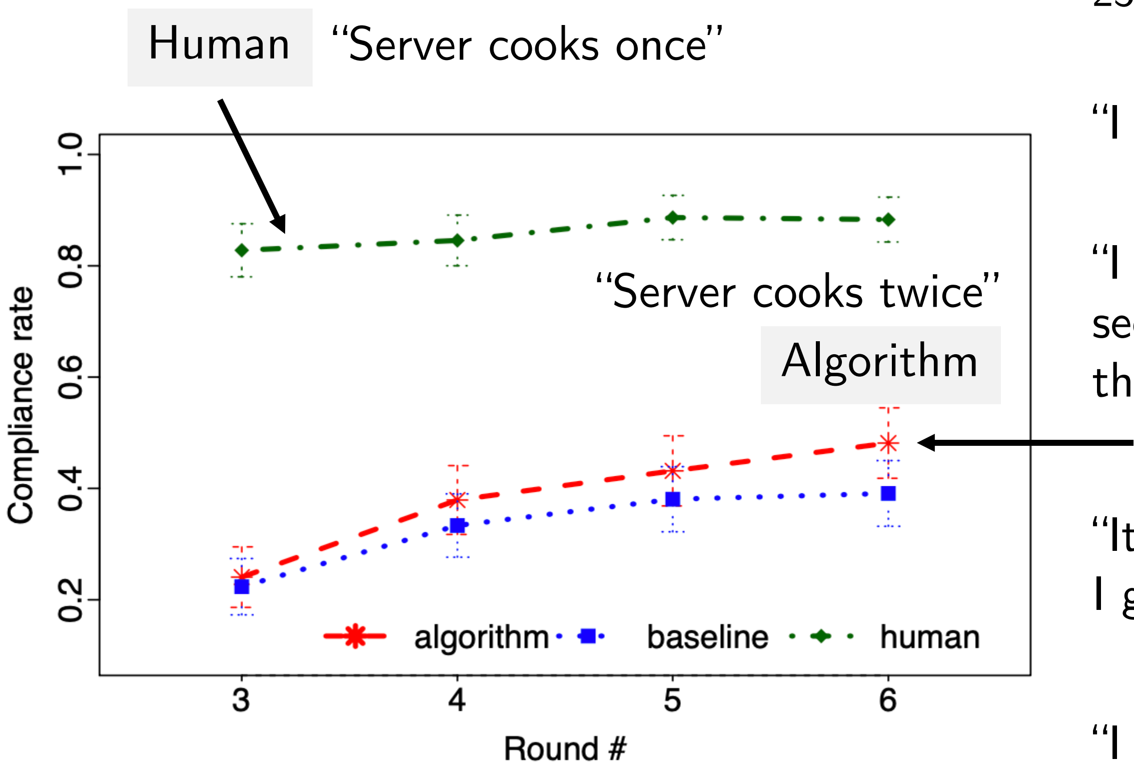


Amazon Mechanical Turk, N = 1,011

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

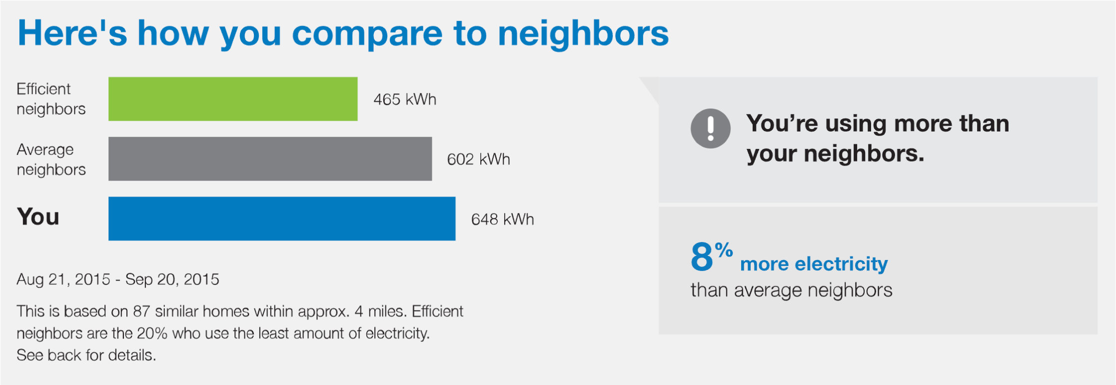
Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Improving Compliance?

Improving Compliance

Social information



Allcott 2011, *Journal of Public Economics*

Improving Compliance

Social information

> "The best players always used this strategy:
> Server cooks twice."

Improving Compliance

Social information

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Incentive to try

Improving Compliance

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Incentive to try

> "You'll earn the maximum bonus
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"Curriculum" – pacing learning

Improving Compliance

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"Curriculum" – pacing learning

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

Improving Compliance

Social information

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"Curriculum" – pacing learning

Algorithm	Human		Hypothetical
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Improving Compliance

Social information

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"Curriculum" – pacing learning

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

Improving Compliance

Interventions based on incentives, social information, and pace

Fraction of participants complying with the optimal tip

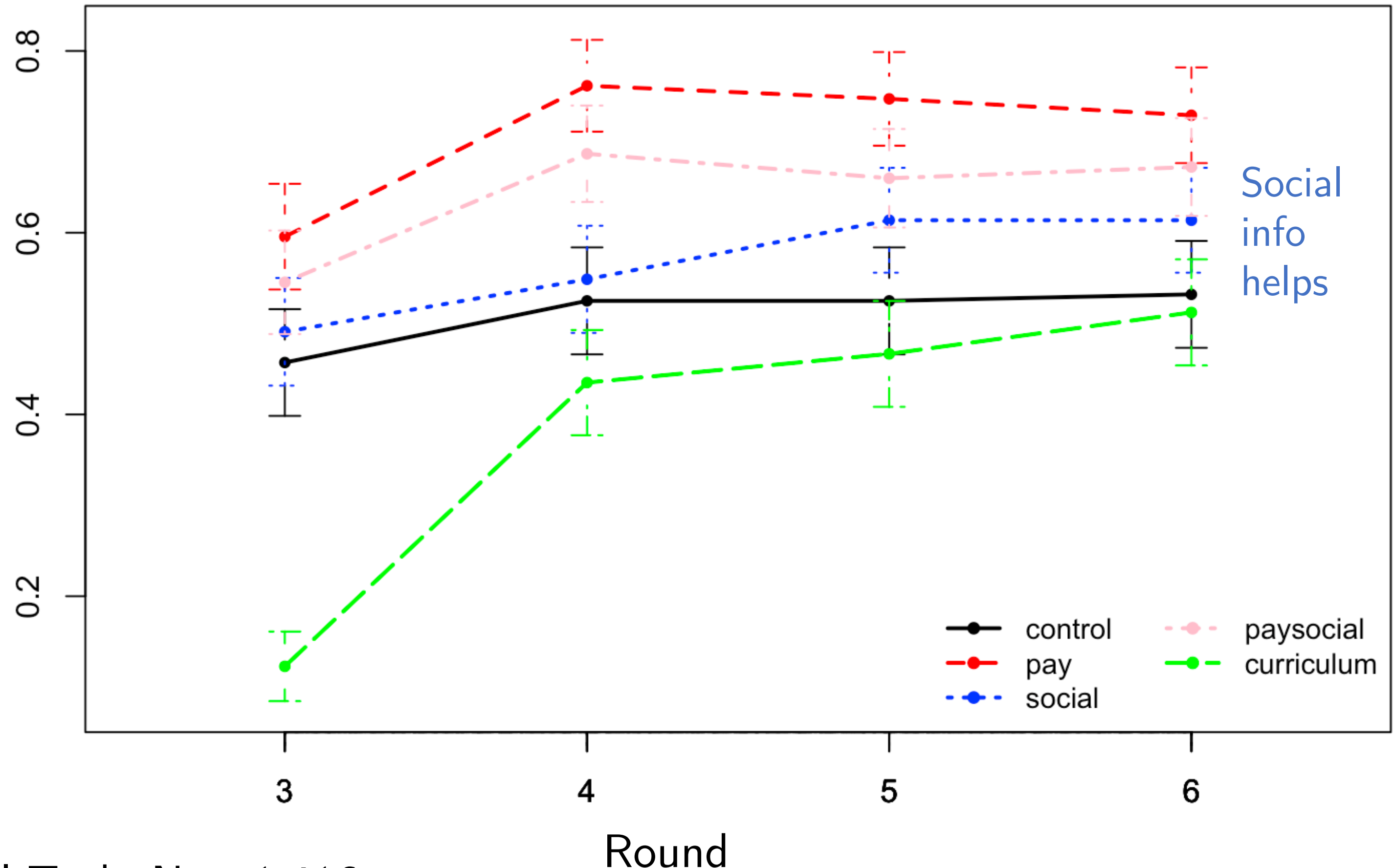
Round

Amazon Mechanical Turk, N = 1,416

Improving Compliance

Interventions based on incentives, social information, and pace

Fraction of participants complying with the optimal tip

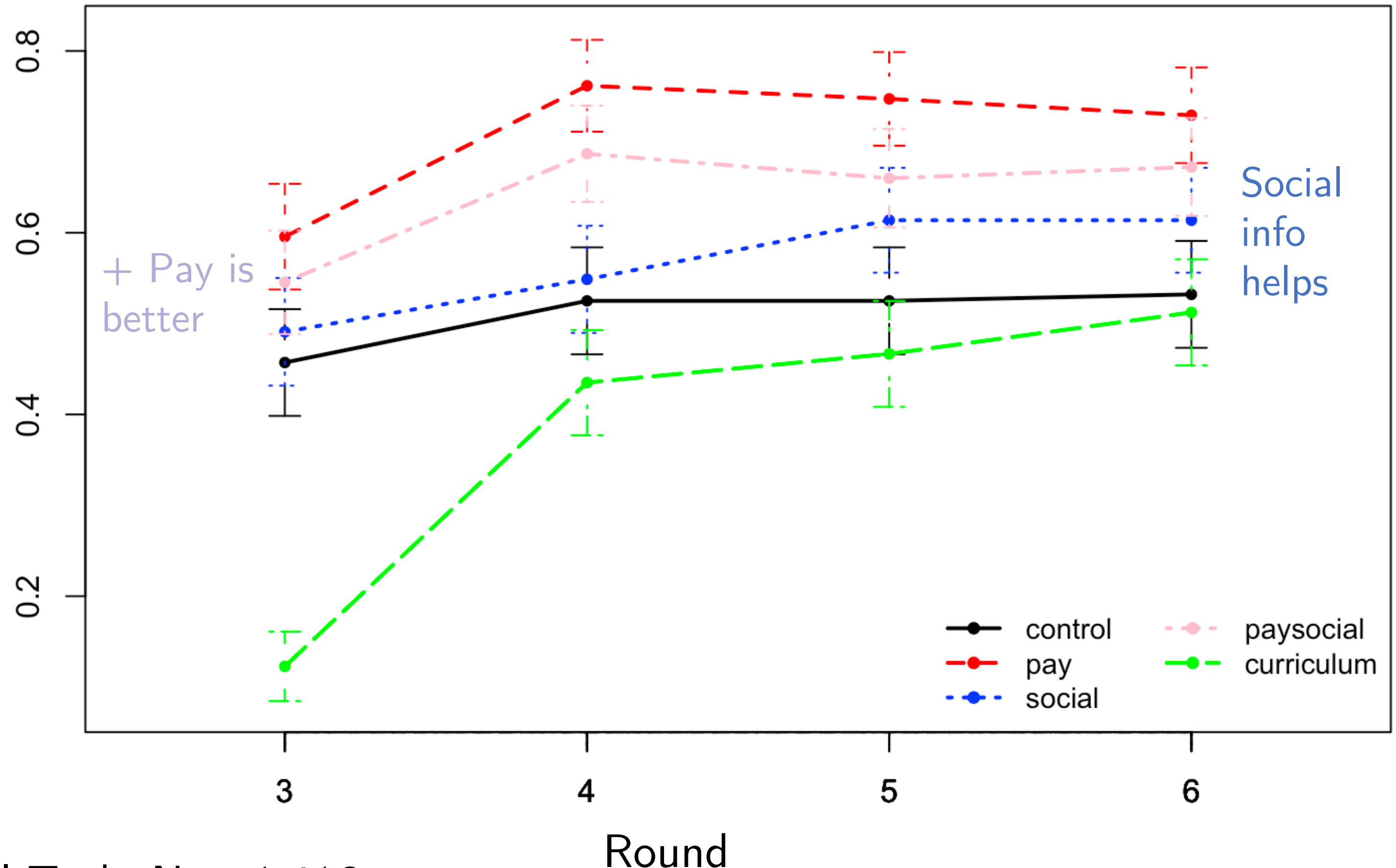


Amazon Mechanical Turk, N = 1,416

Improving Compliance

Interventions based on incentives, social information, and pace

Fraction of participants complying with the optimal tip

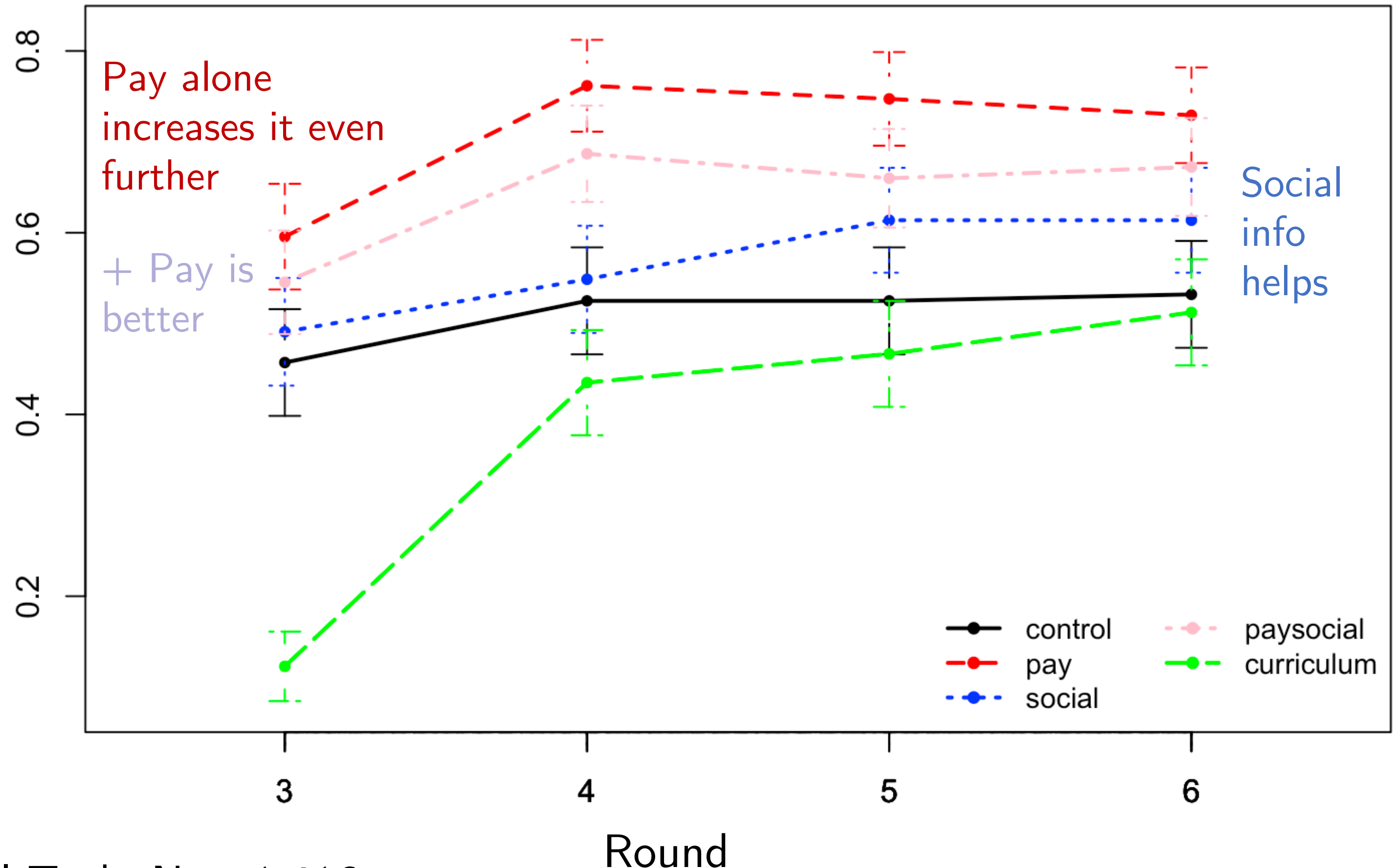


Amazon Mechanical Turk, N = 1,416

Improving Compliance

Interventions based on incentives, social information, and pace

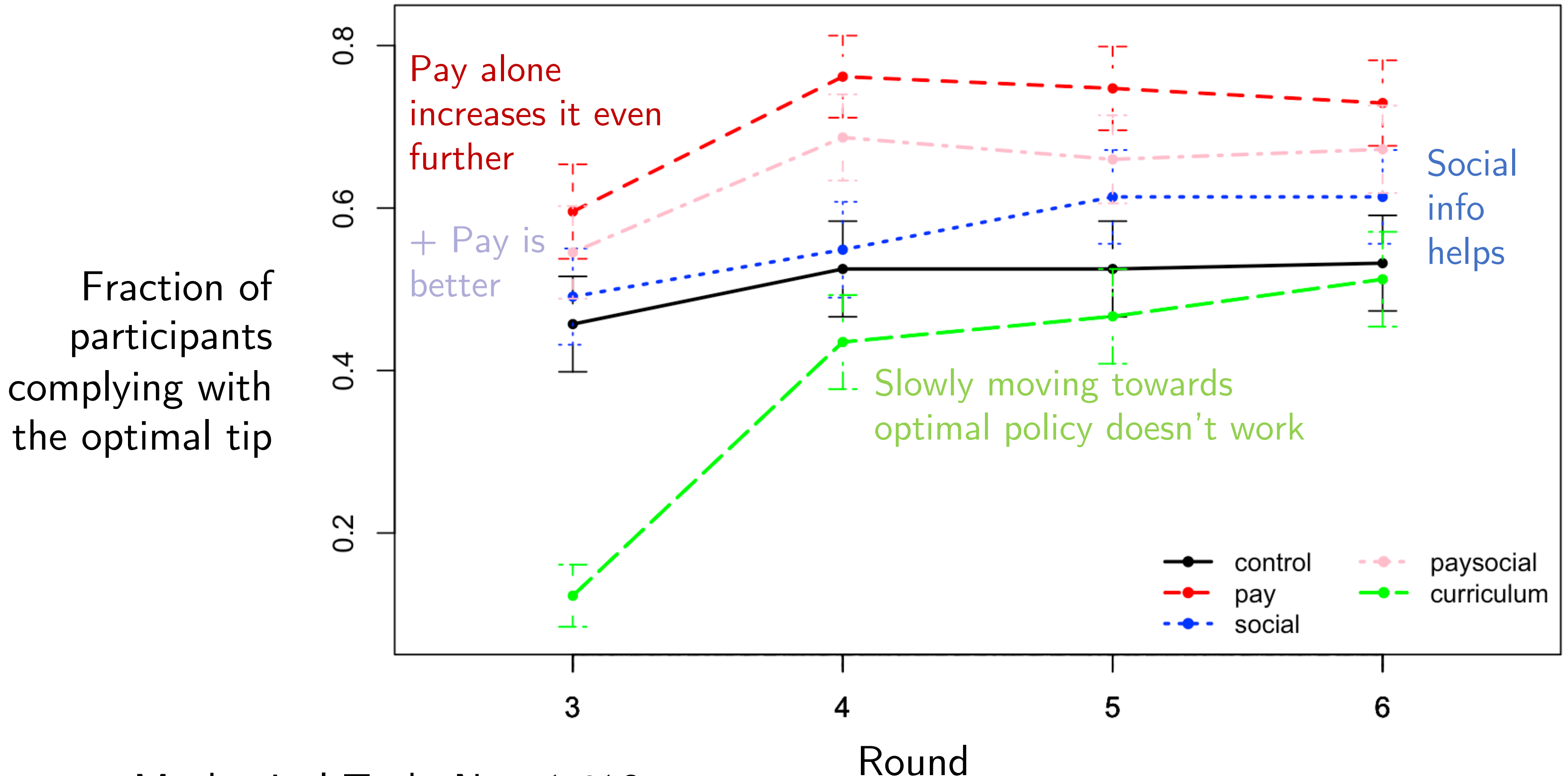
Fraction of participants complying with the optimal tip



Amazon Mechanical Turk, N = 1,416

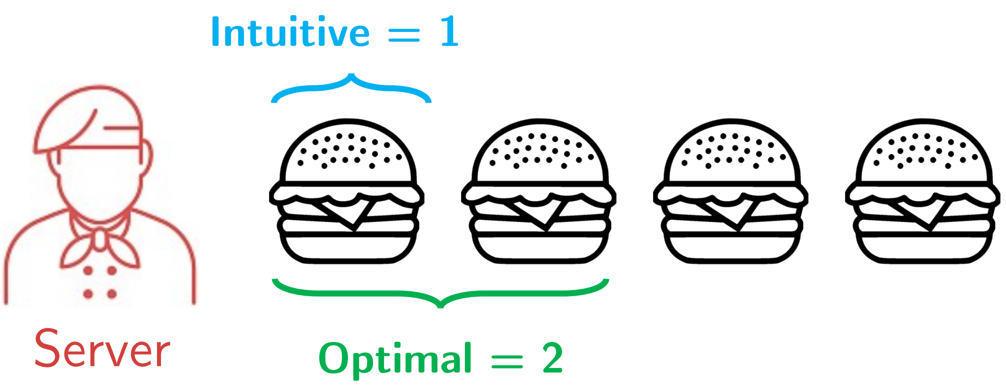
Improving Compliance

Interventions based on incentives, social information, and pace



Amazon Mechanical Turk, N = 1,416

Study 1:



What If Decisions Are More Granular?

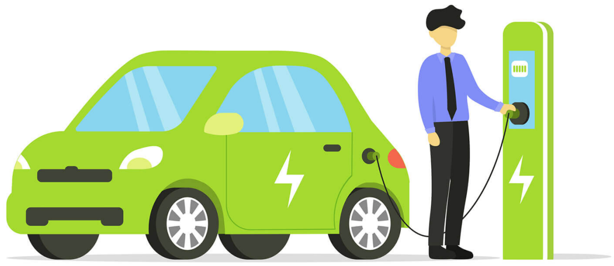
What If Decisions Are **More Granular**?

Also, What If Things Are **Uncertain**?

Study 2:

What If Decisions Are More Granular?

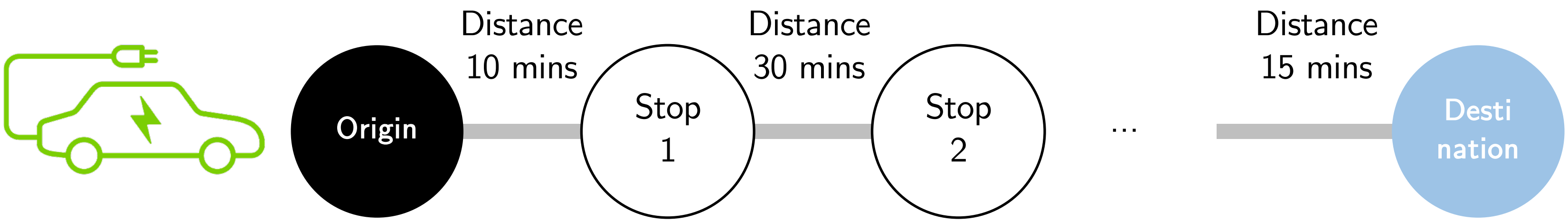
Also, What If Things Are Uncertain?



Study 2:

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

EV Charging Game



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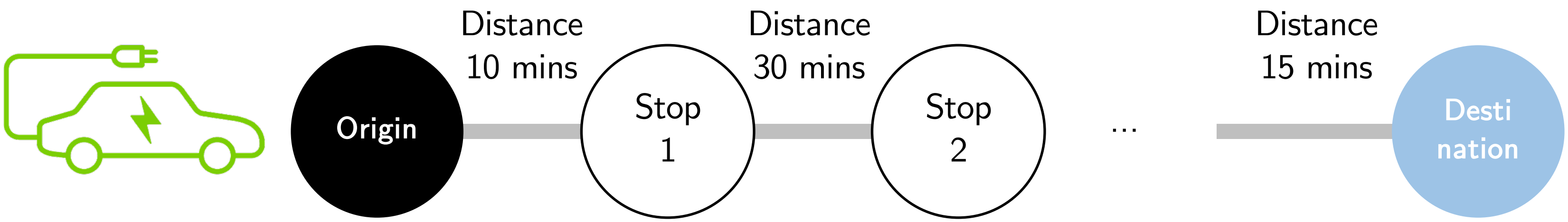

Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Study 2:

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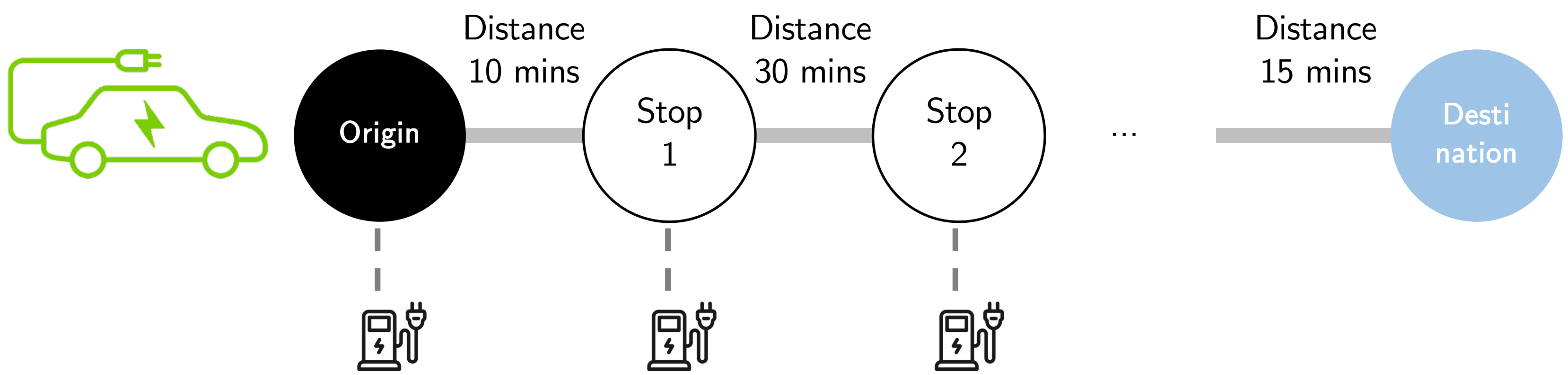
EV Charging Game



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

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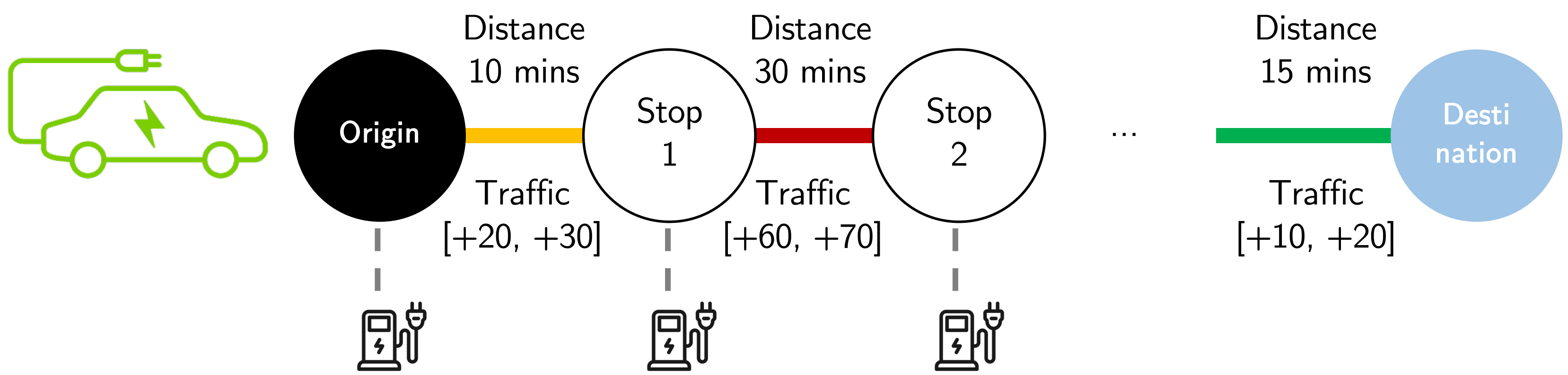

Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Challenges: Even without traffic, the amount of initial charge won't be enough
+ Uncertain traffic, uniformly distributed within the specified range

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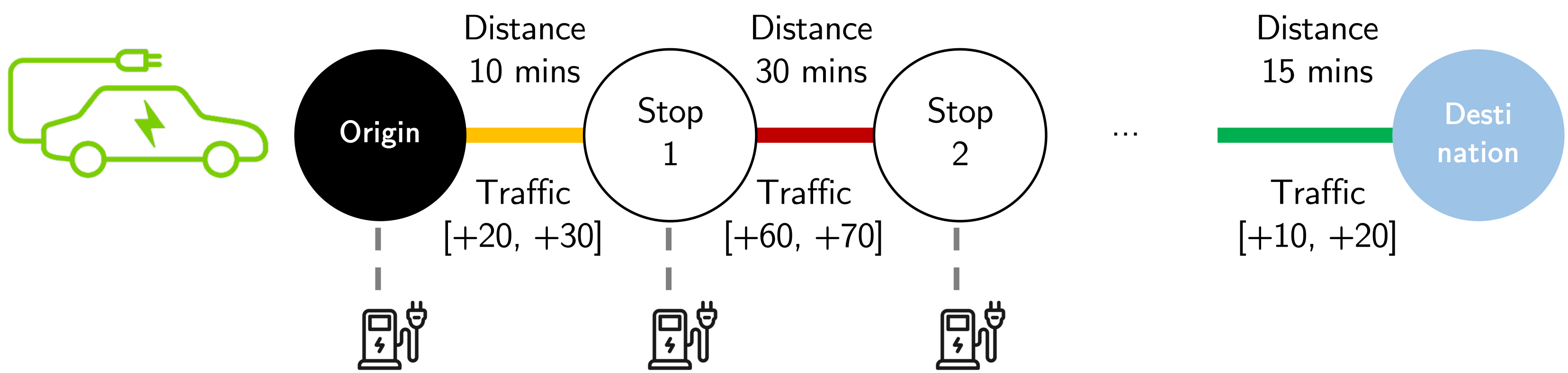
EV Charging Game



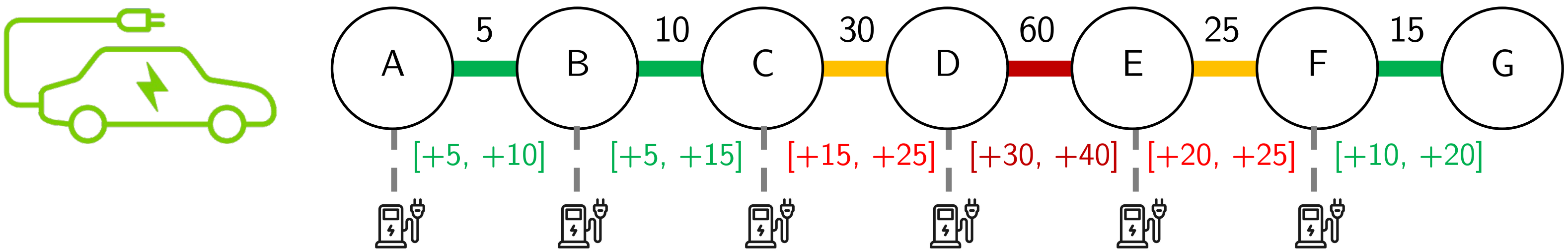
Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

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

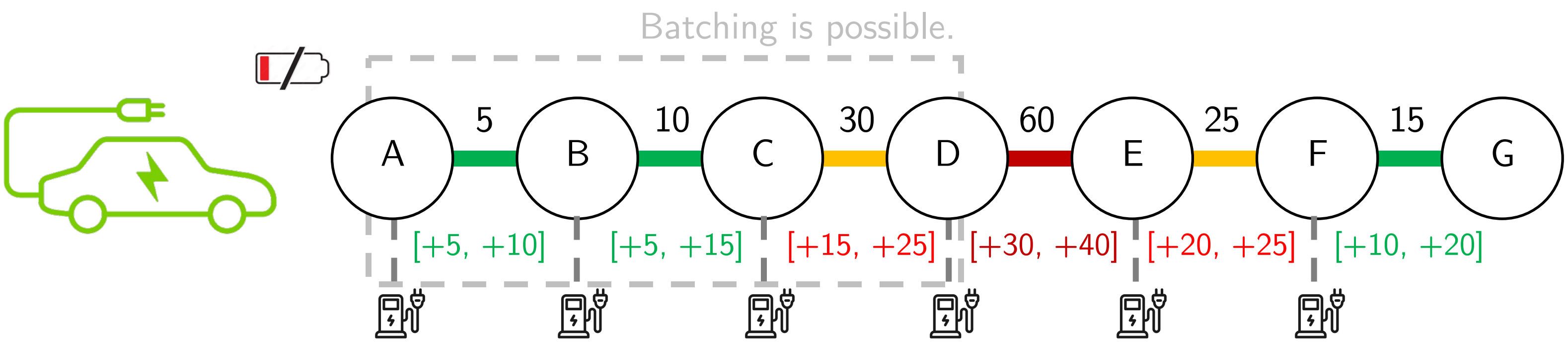
+ Uncertain traffic, uniformly distributed within the specified range
+ Cost to exit to charge **(+30 mins)** and nonlinear charging time
+ Penalty if running out of charge in the middle **(+300 mins)**

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

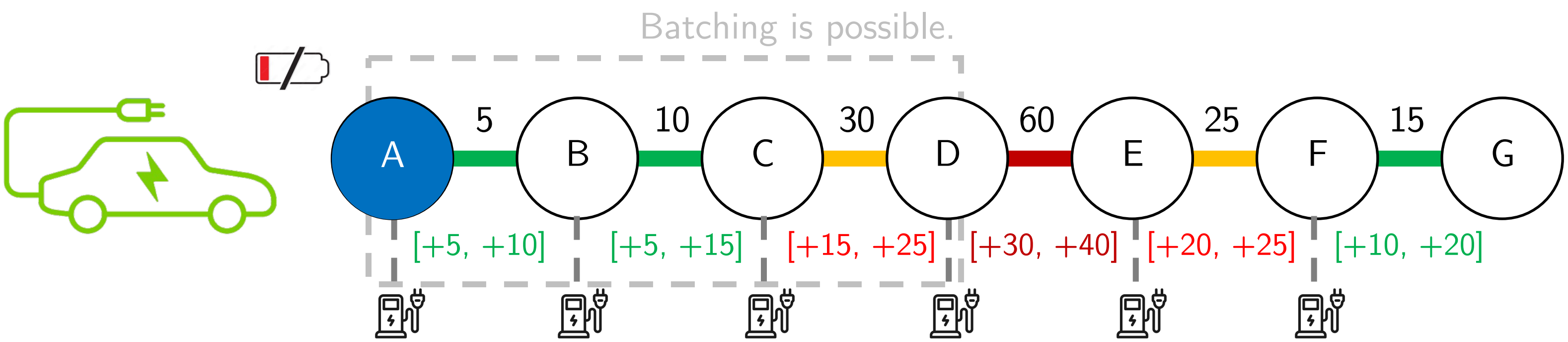
Design To Batch, or Not to Batch



Design To Batch, or Not to Batch



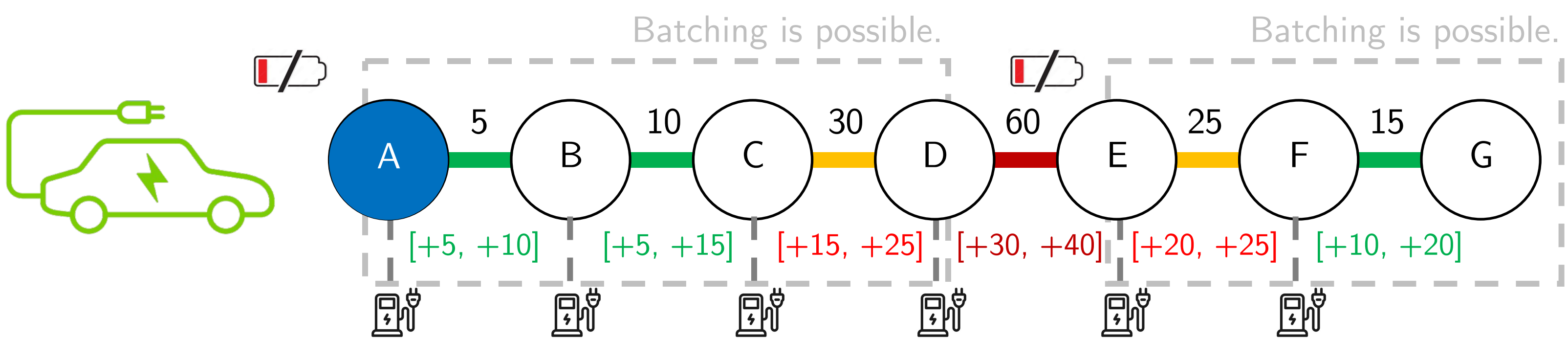
Design To Batch, or Not to Batch



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.

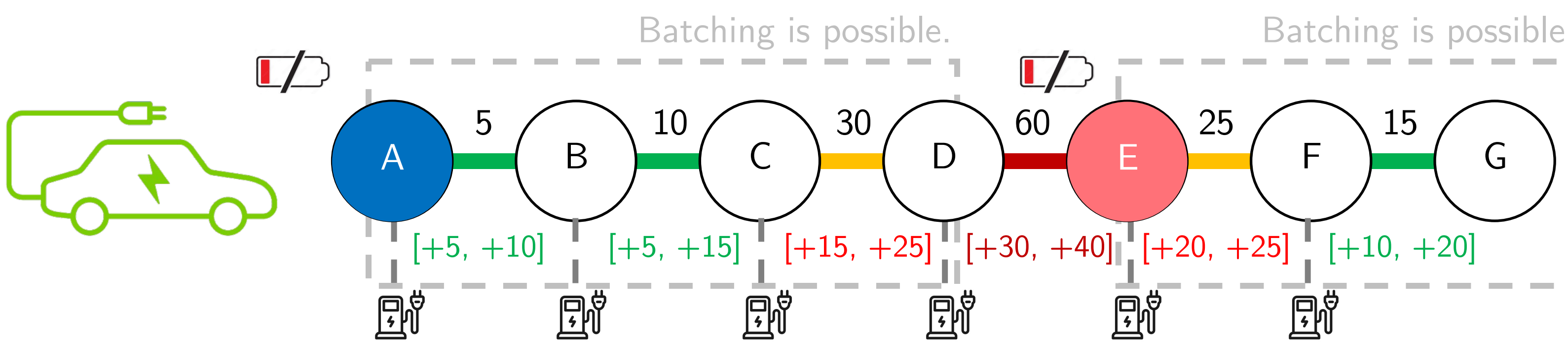
Design To Batch, or Not to Batch



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.

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

Design To Batch, or Not to Batch



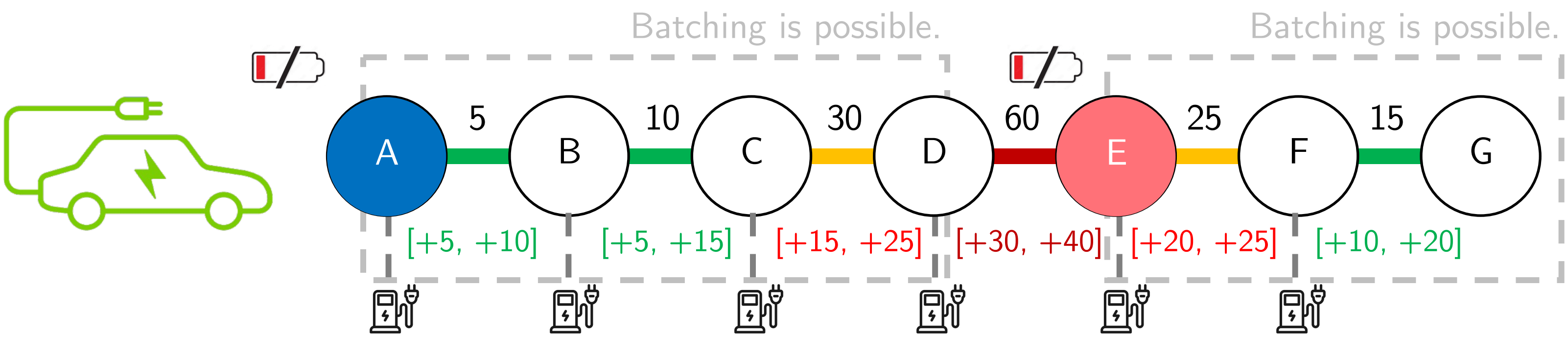
A Optimal is to **"batch"** the required charges for the next two stops (A → C) rather than just A → B or further batch A → D.

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 2A:

Design Flow

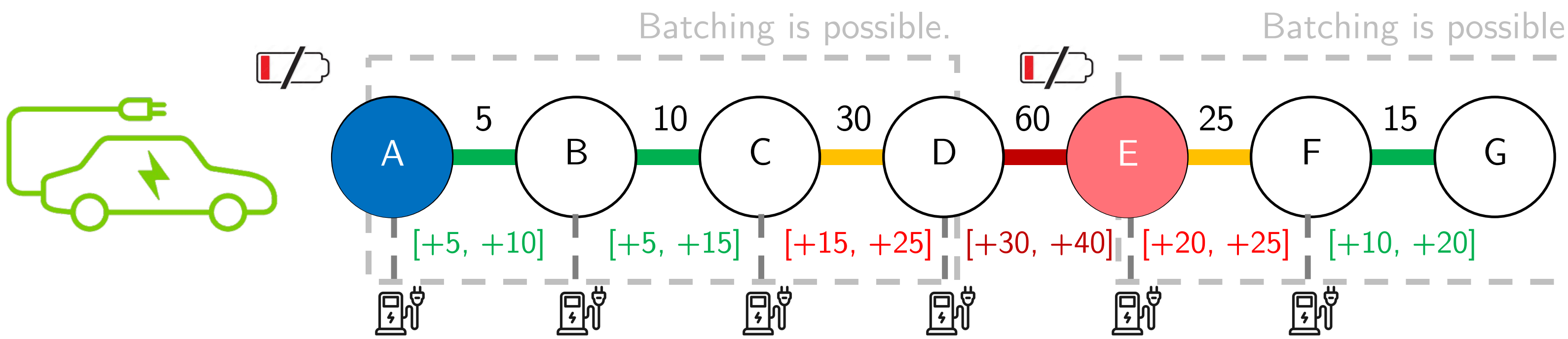


Performance: Time to destination

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

Study 2A:

Design Flow



Performance: Time to destination

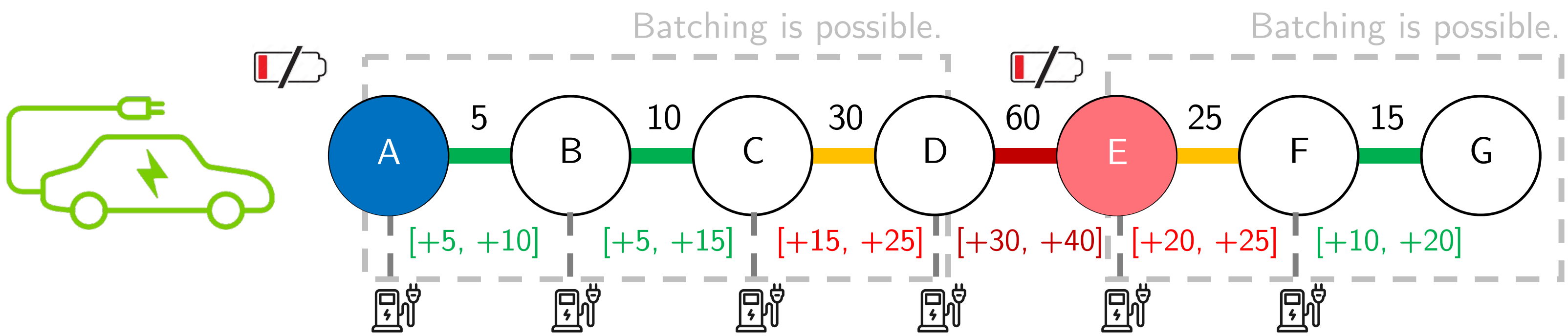
Round 1	Round 2

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

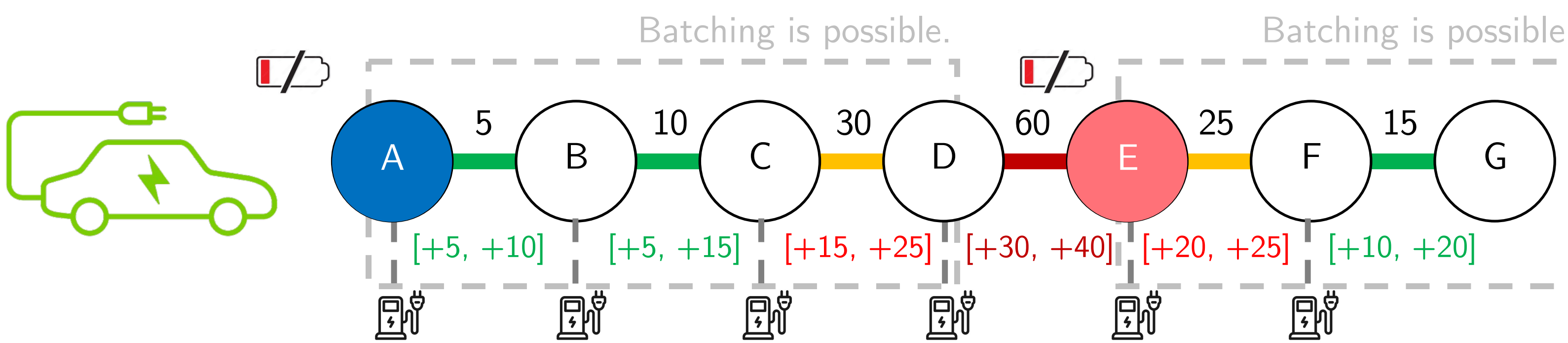
Round 1	Round 2	Round 3 (+ tip)	Round 4 (+ tip)

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



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

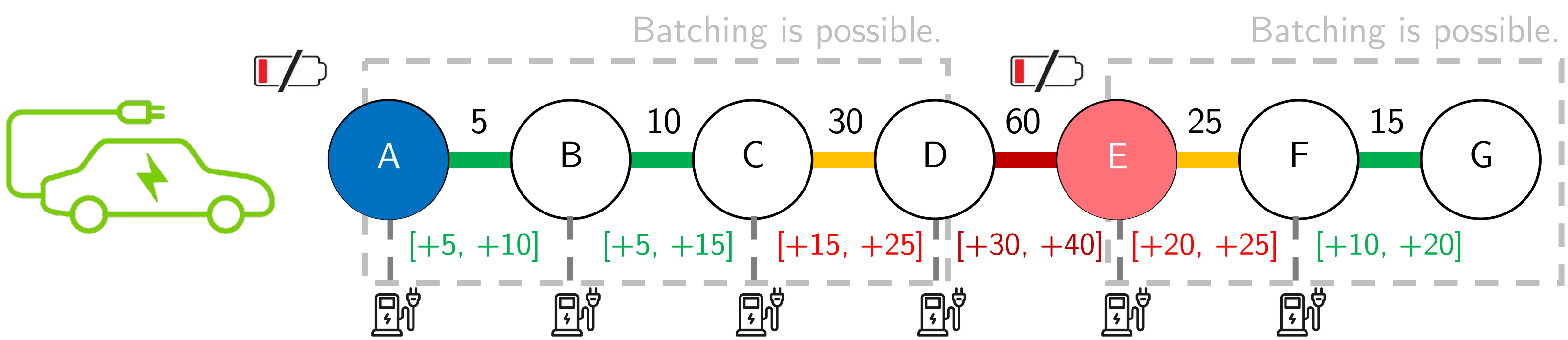
At every stop, we present either...

Precise Tip:

You should exit and charge X%

Study 2A:

Design Tip Conditions



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"Split" You should charge enough for this segment

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Study 2A:

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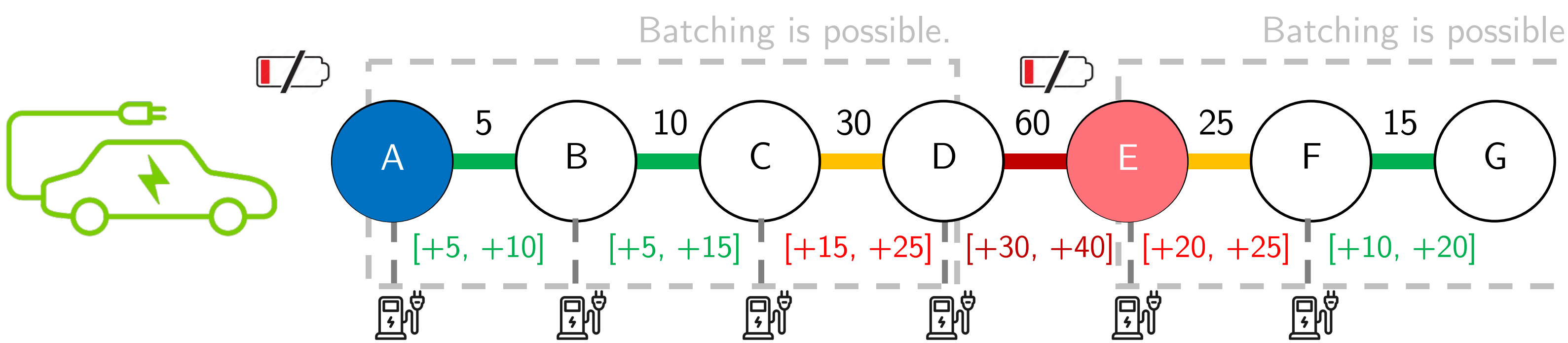

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At every stop, we present either...

Precise Tip:

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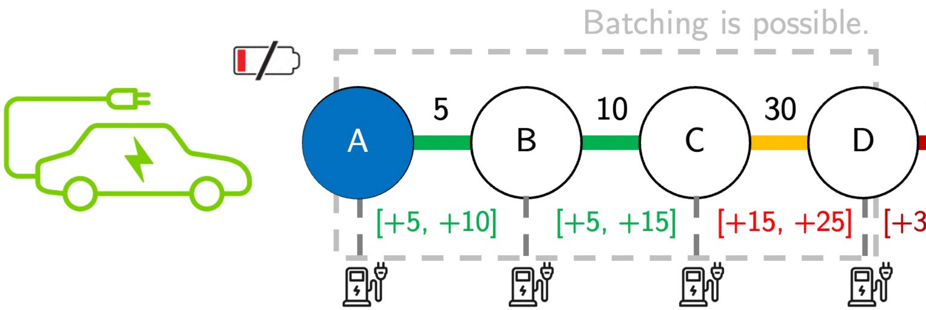
Broad Tip:

"Split" You should charge enough for this segment

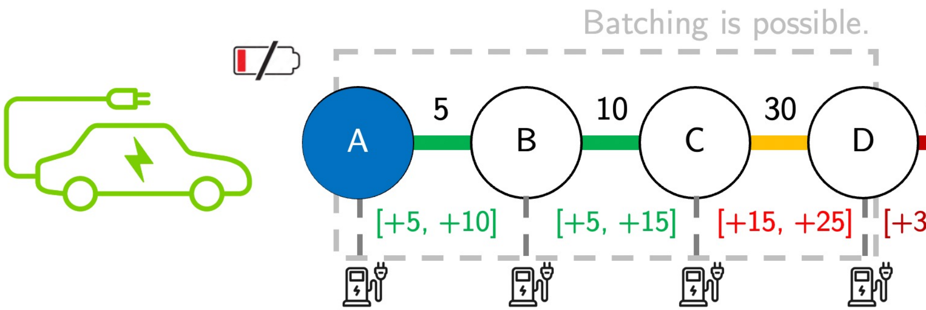
"Batch" You should charge enough for this segment + next one

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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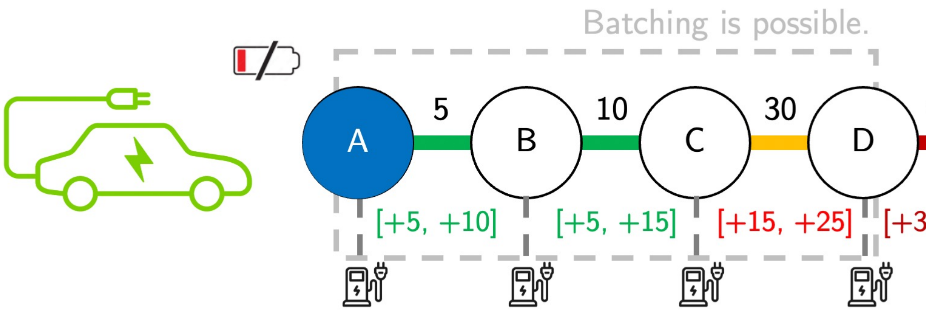
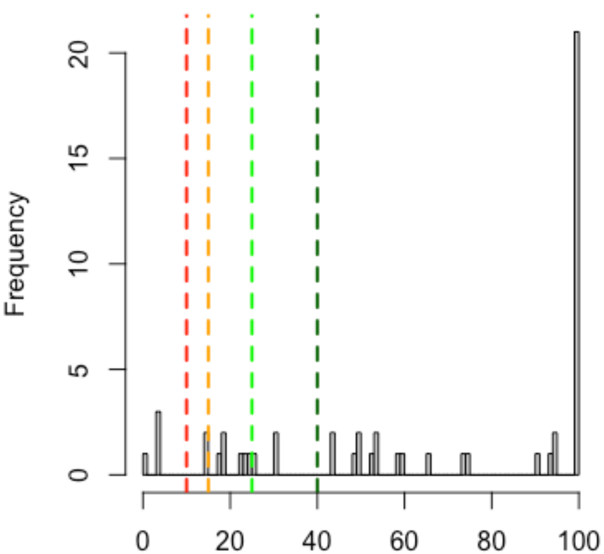
Aftercharge
= amount of charge after re-charging

Study 2A:

Results Wide Range of Decisions



Round 1



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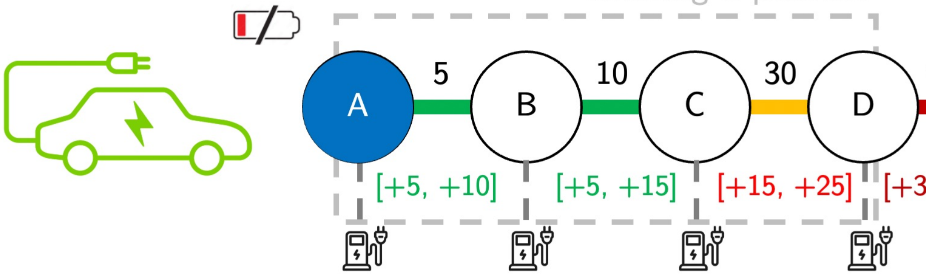
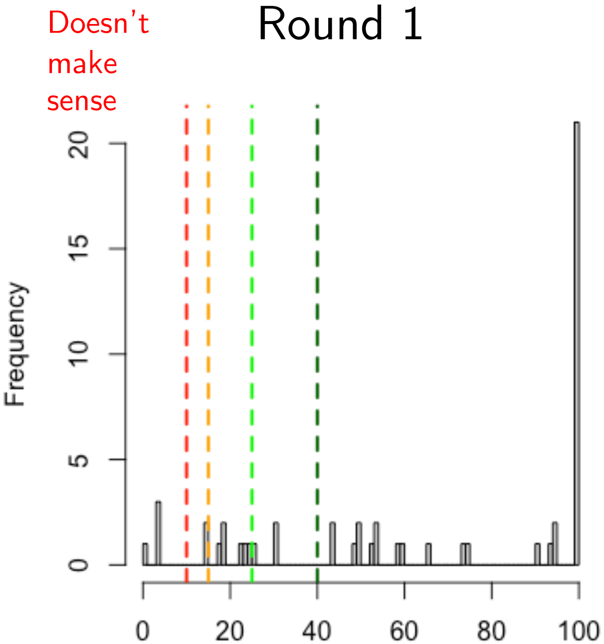


Doesn't make sense



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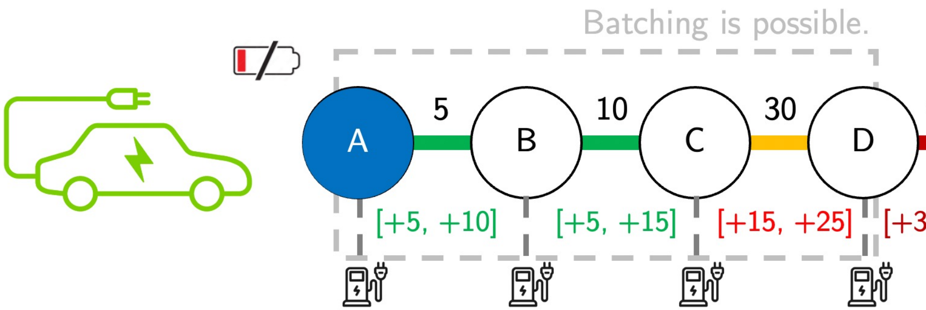

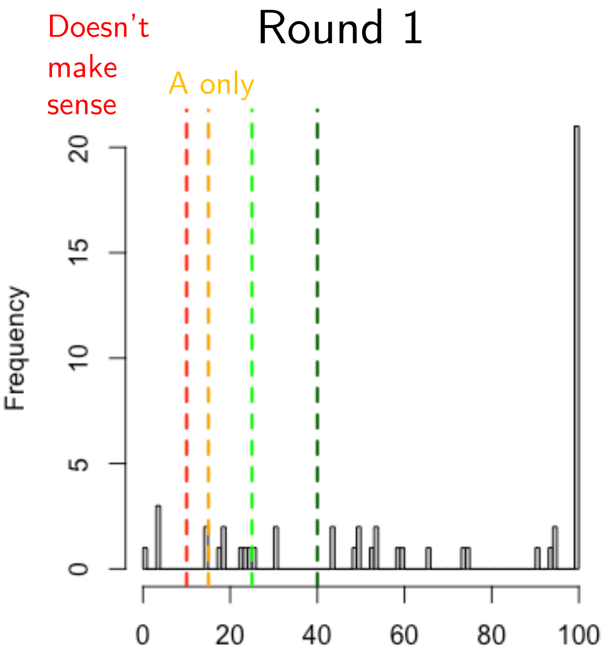

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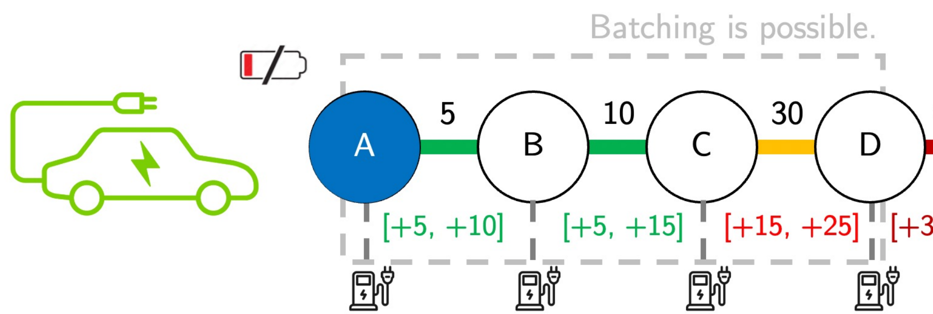

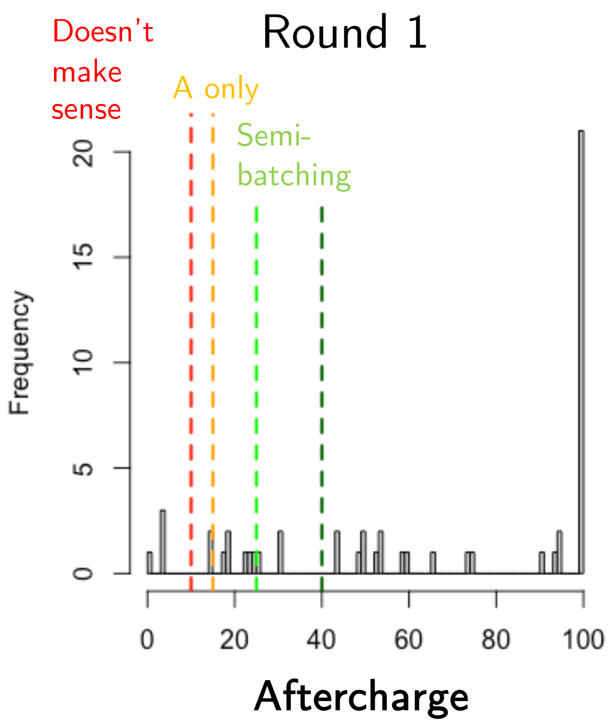

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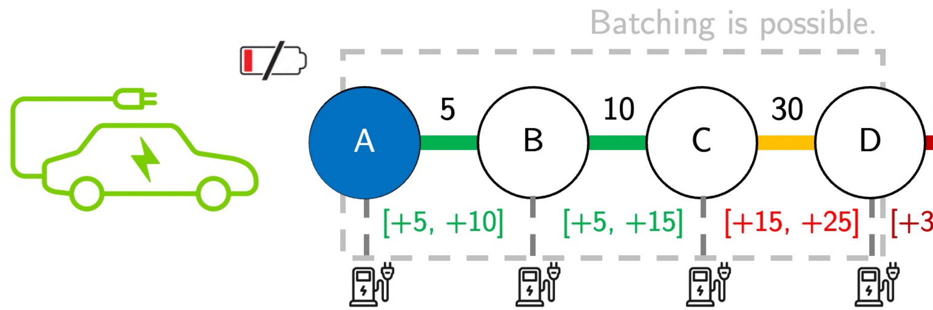

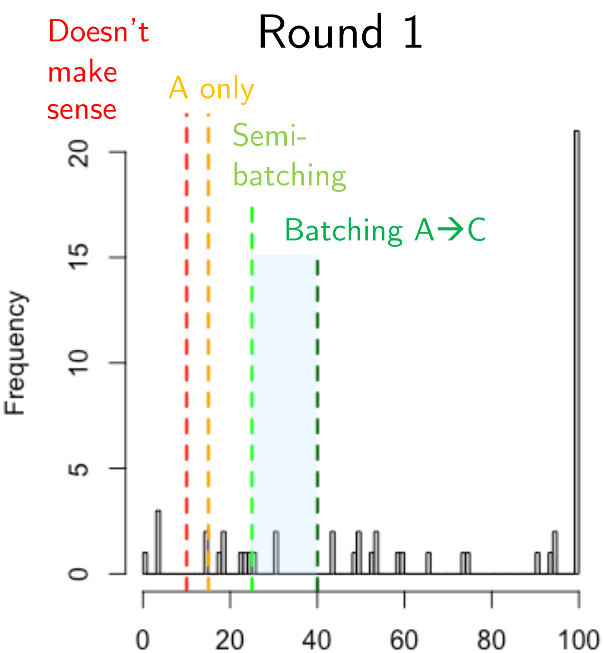

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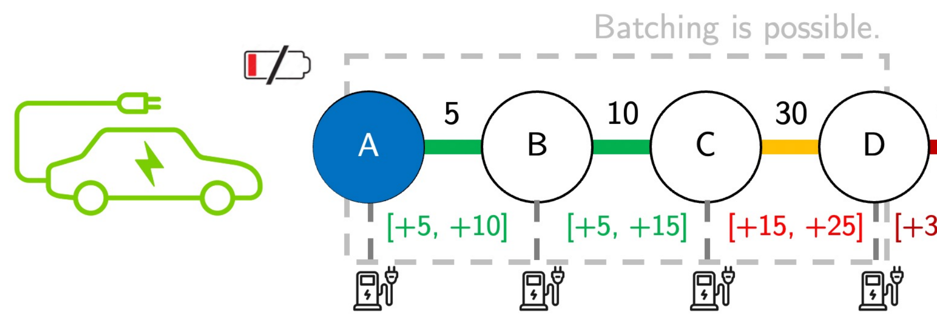

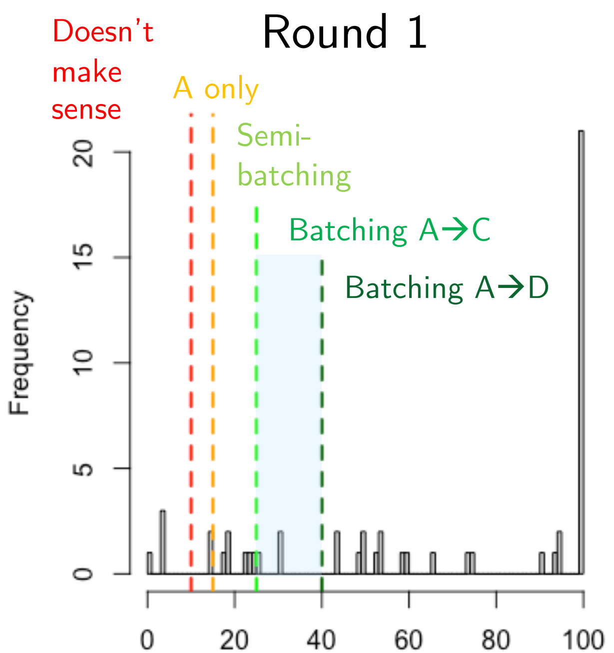

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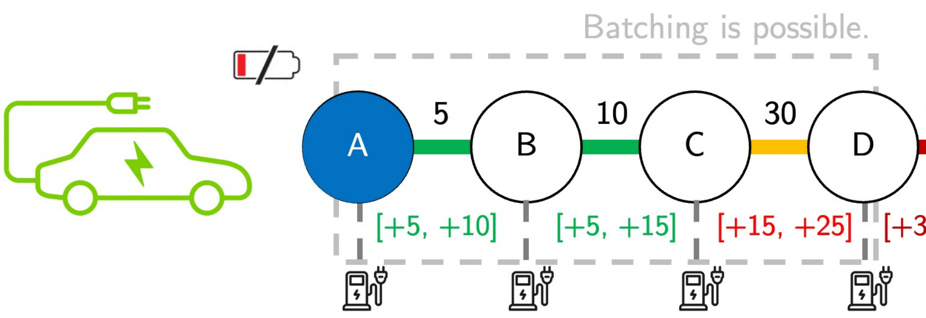

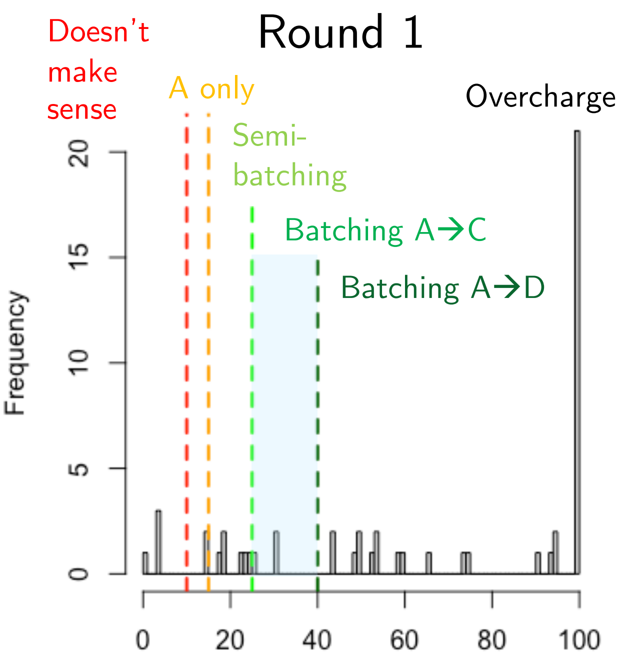

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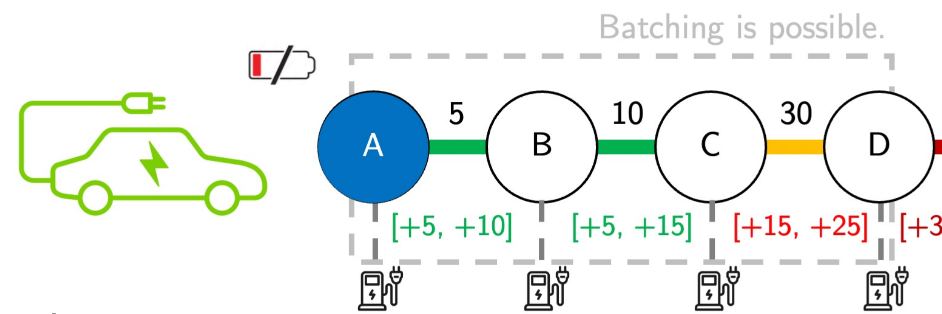
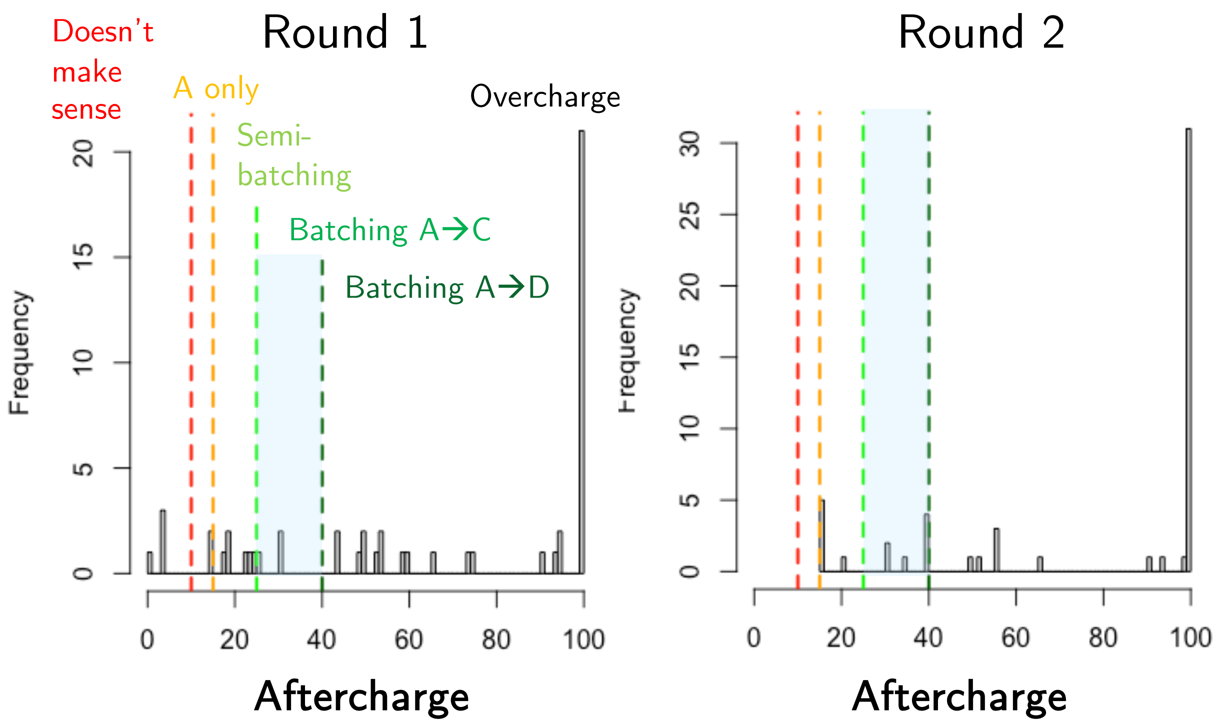
Study 2A:

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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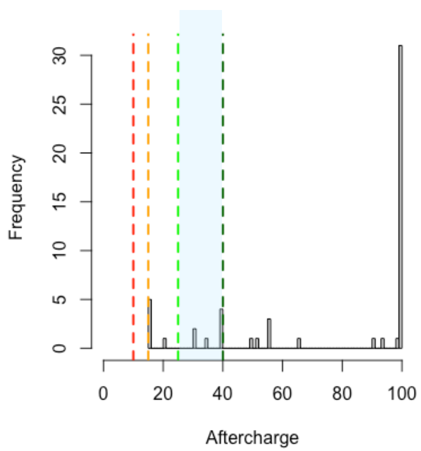
("aftercharge" = 25-40)

In one round, everyone learned to do at least semi-batching for this exit.

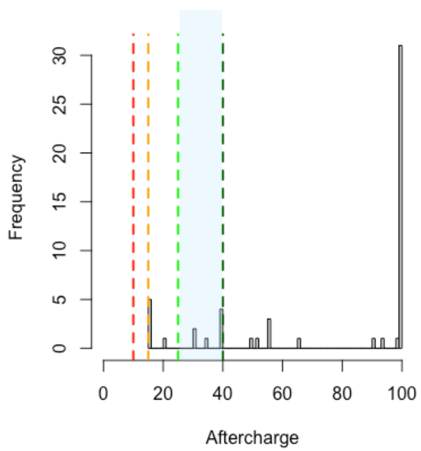
Results What Happened After Tip?

Round 2

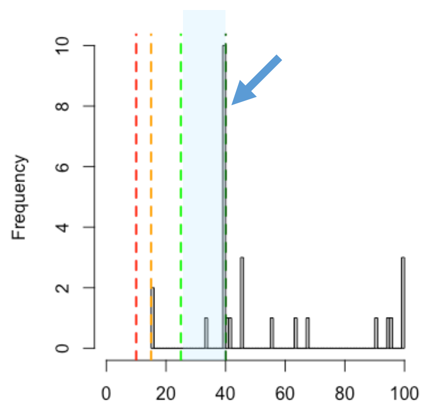


Results

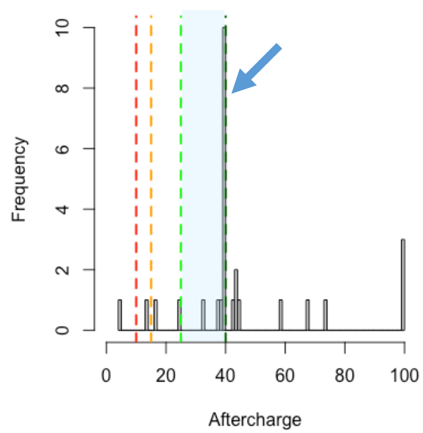
Round 2



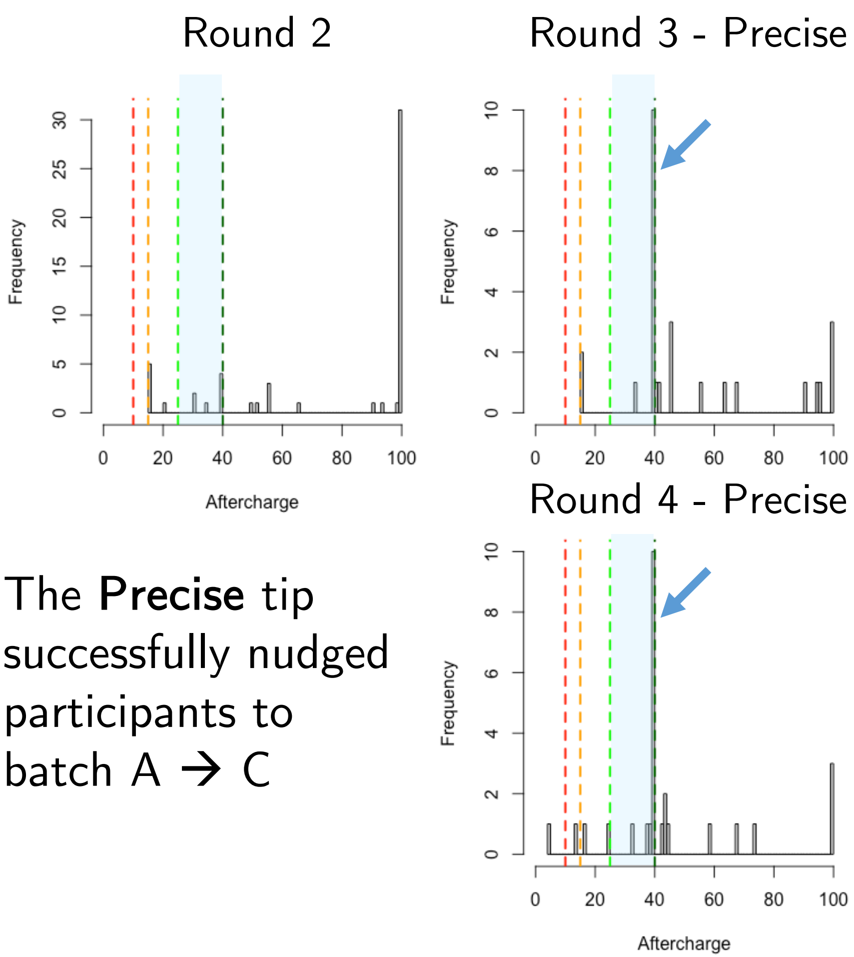
Round 3 - Precise



Round 4 - Precise



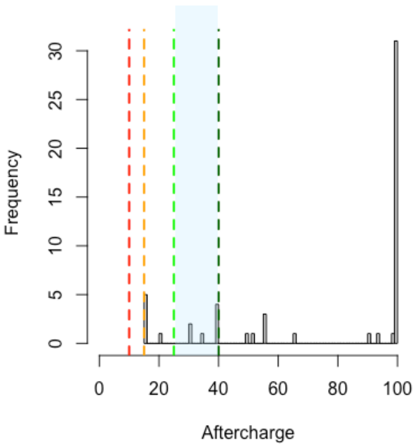
Results Precise Tip Worked (as Expected)



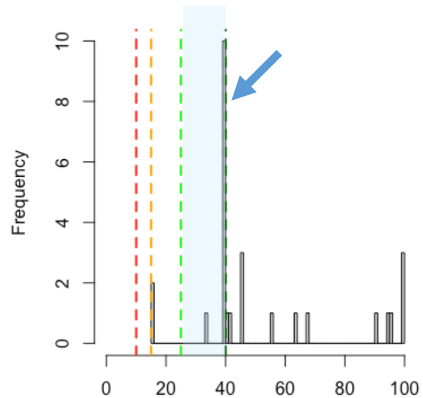
The **Precise** tip successfully nudged participants to batch A → C

Results

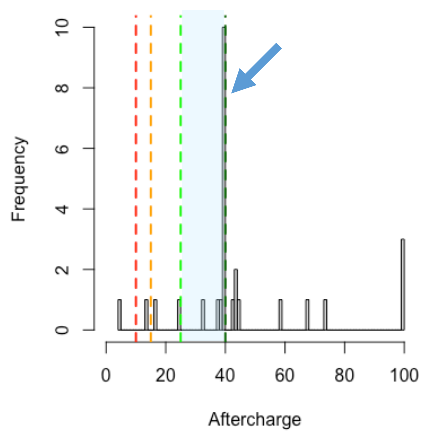
Round 2



Round 3 - Precise



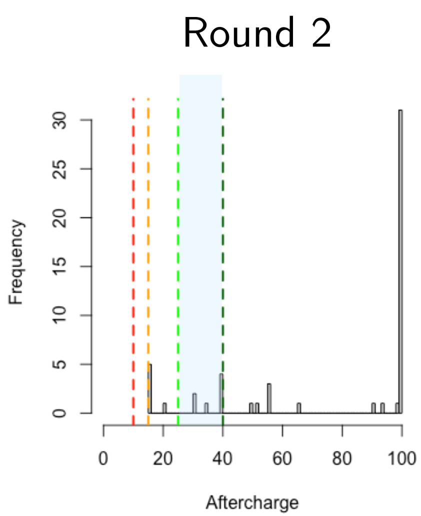
Round 4 - Precise

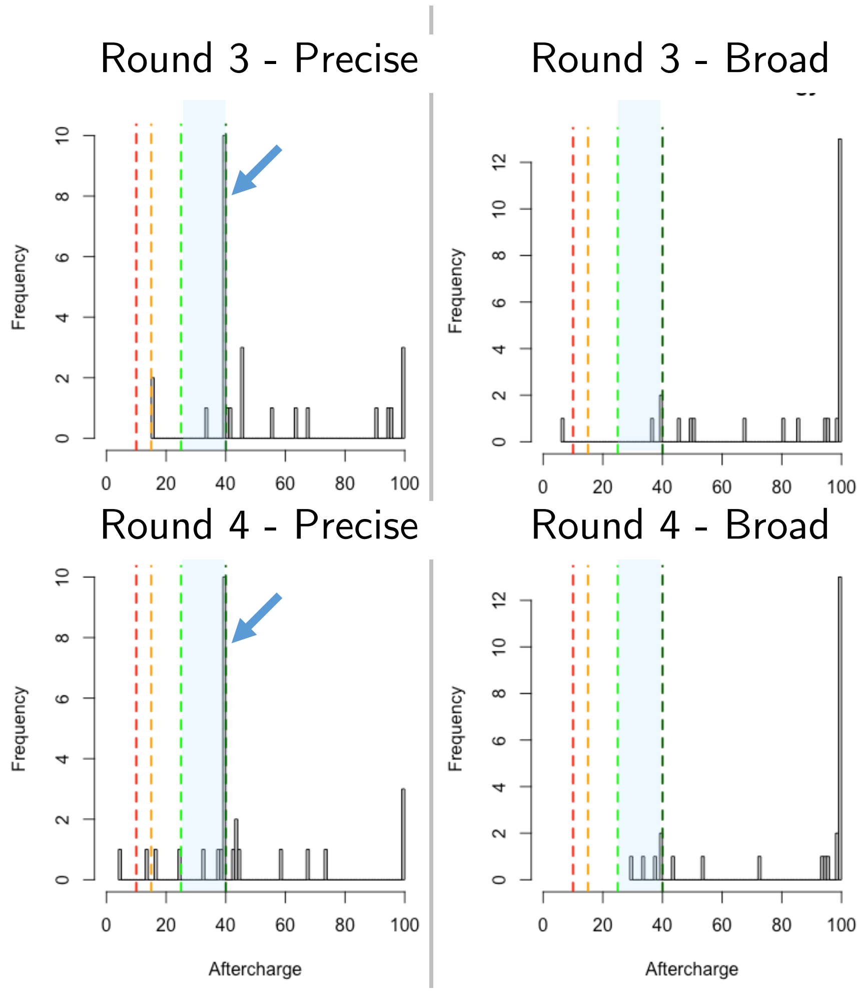


The **Precise** tip successfully nudged participants to batch A → C

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

Results Broad Tip Kind of Failed



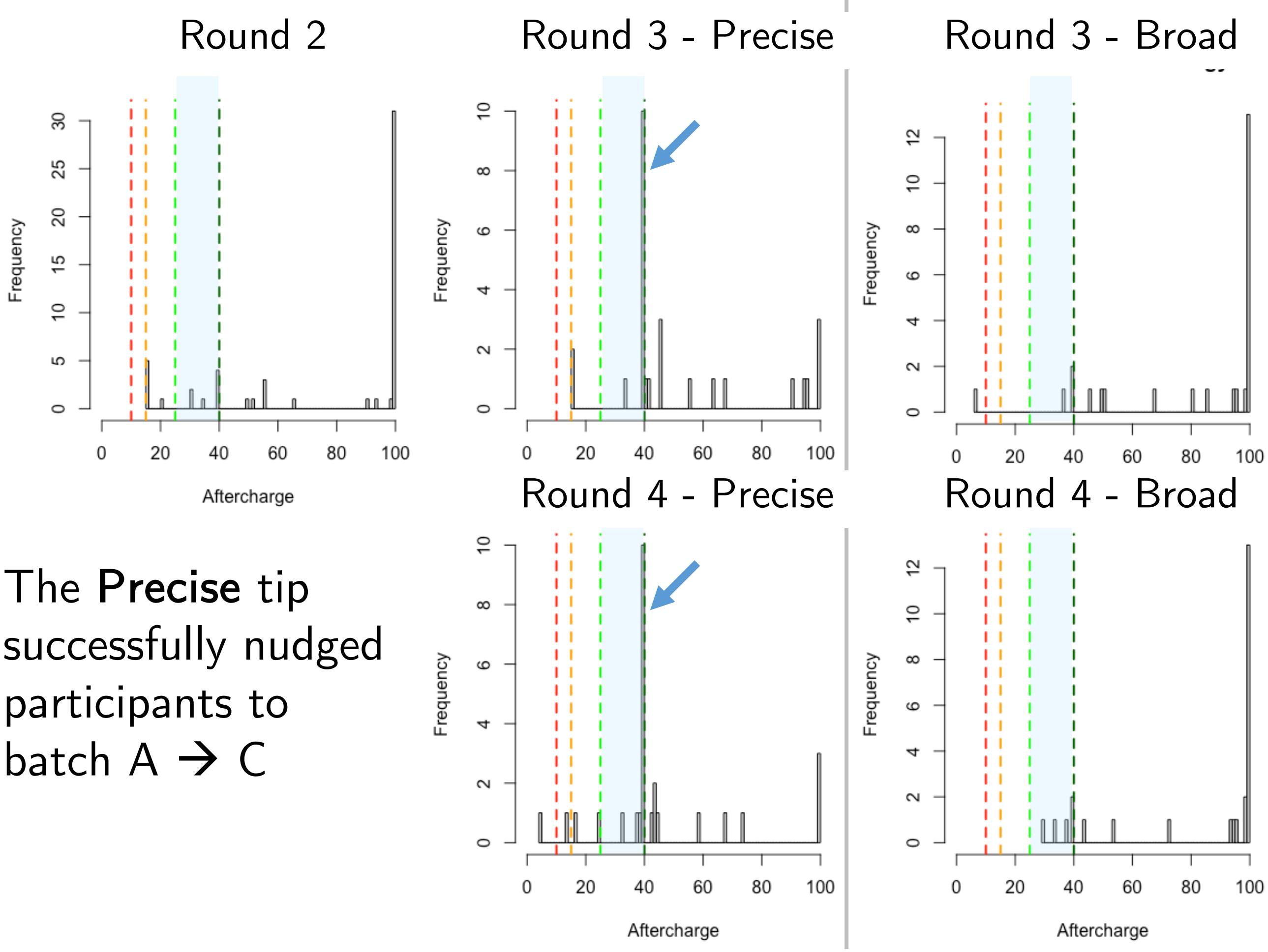


Broad tip
"You should charge enough for this segment and the next one"

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



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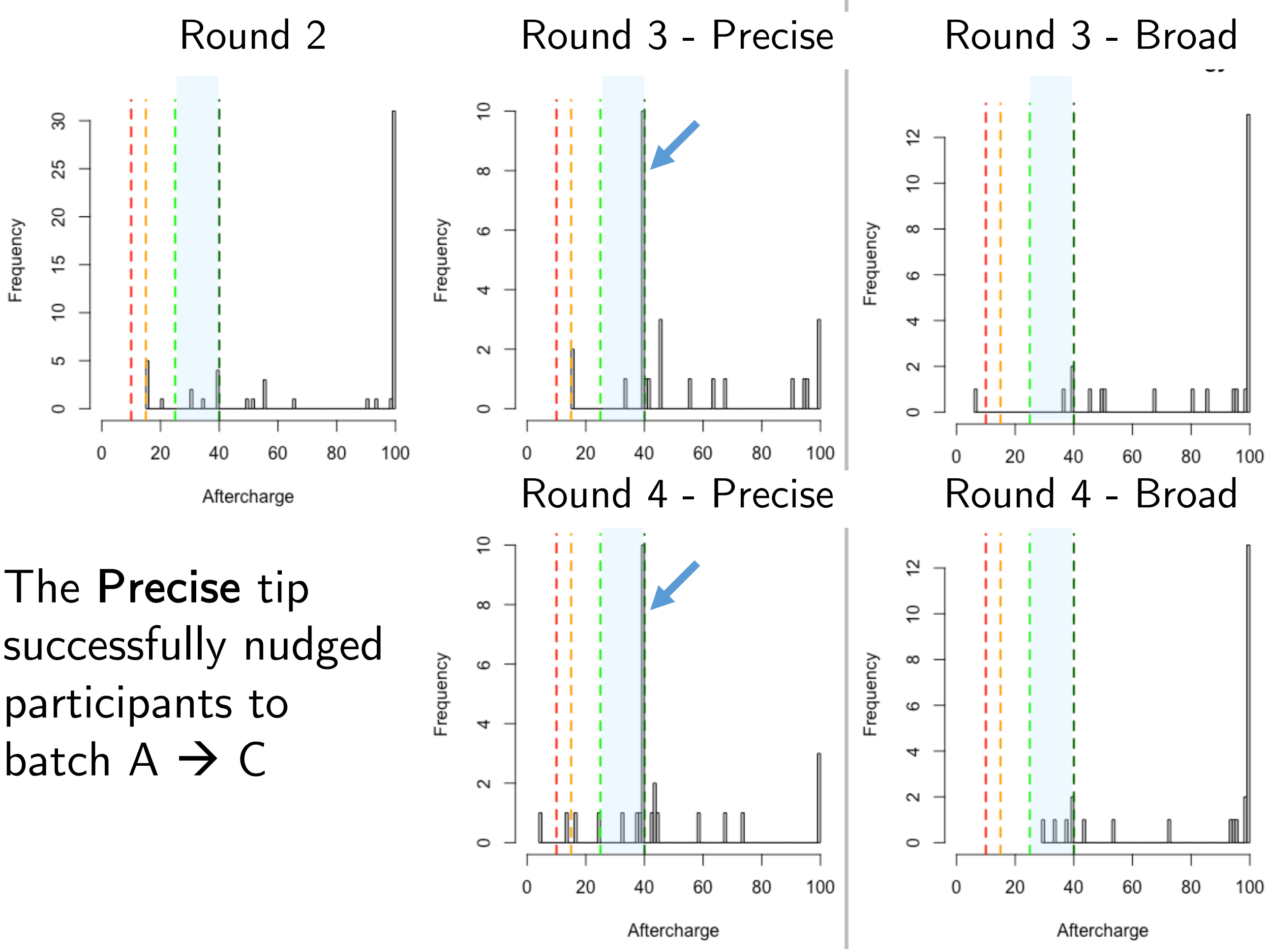
Q: Could it be due to the tip being perceived as counterintuitive?

Results Broad Tip Kind of Failed



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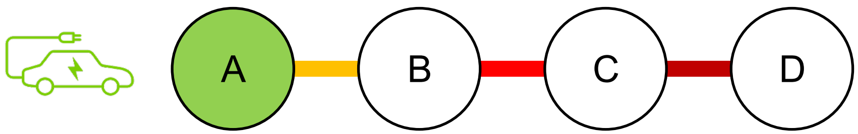
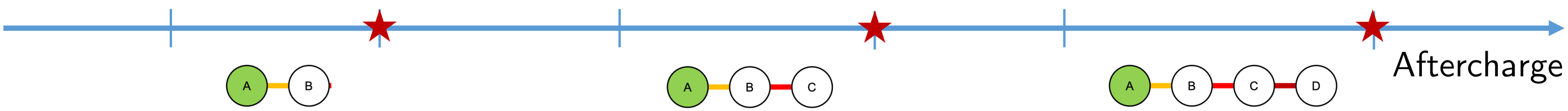
The **Precise** tip successfully nudged participants to batch A → C

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

Q: Did Precise tip help people learn?

Classifying Decisions





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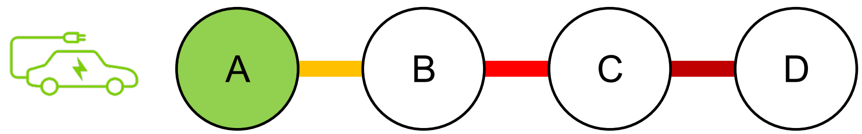

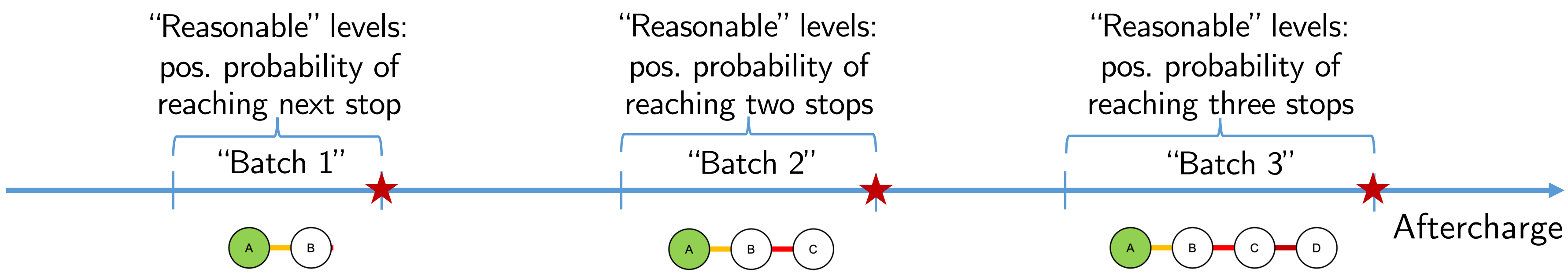

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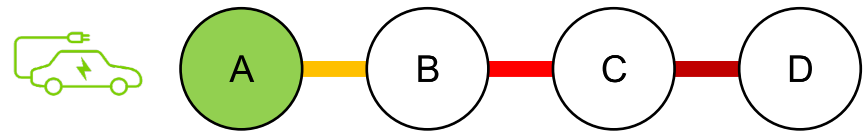
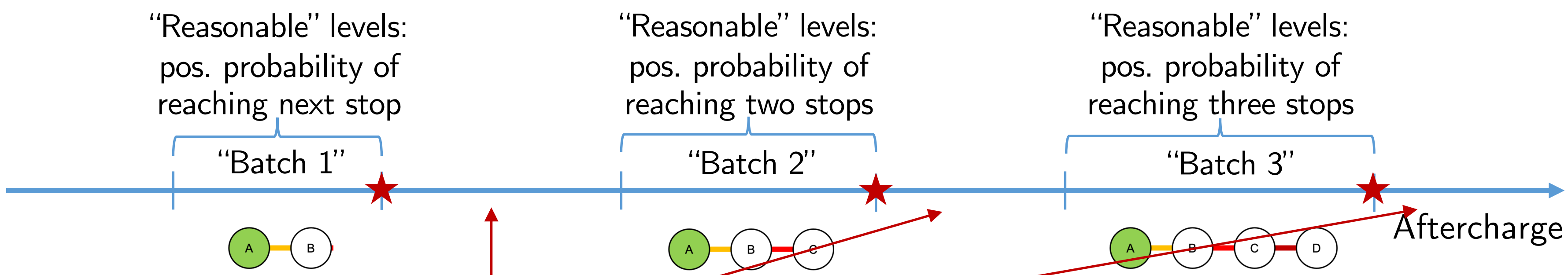
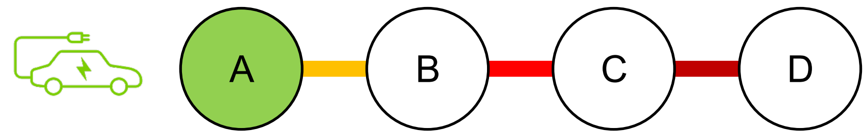
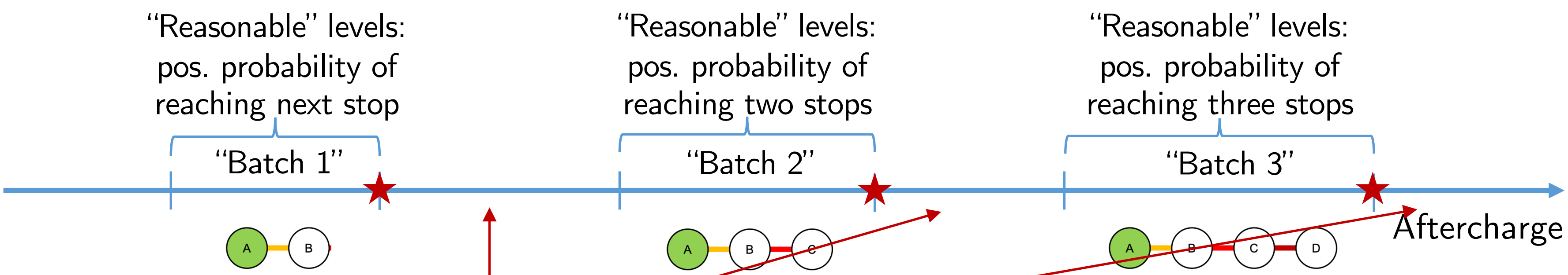




Too little charge for next "batch",
but too much for current…
…but **most charging here**
(risk aversion, limited look-ahead)
→ unnecessarily conservative

Classifying Decisions





Too little charge for next "batch",
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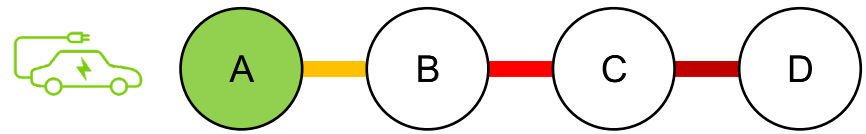
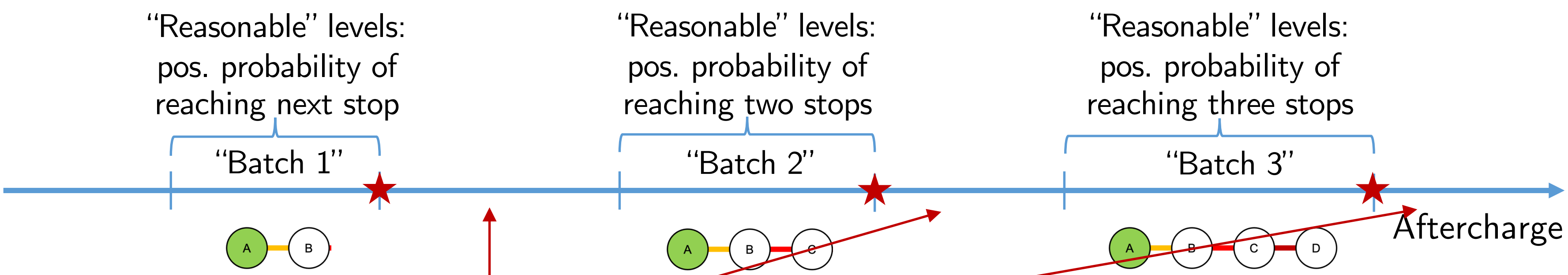
Hierarchical model of decision-making:

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

Classifying Decisions





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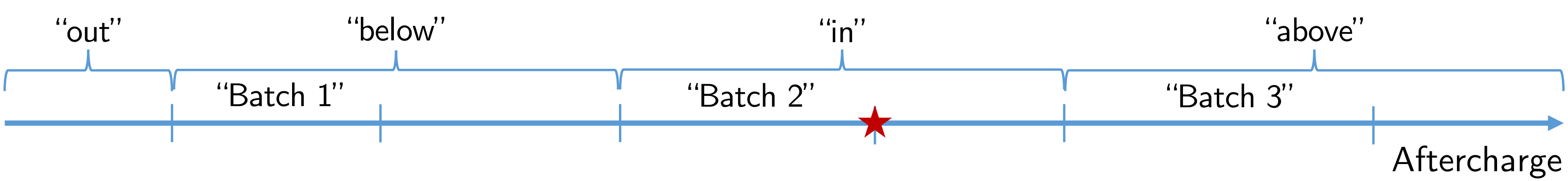

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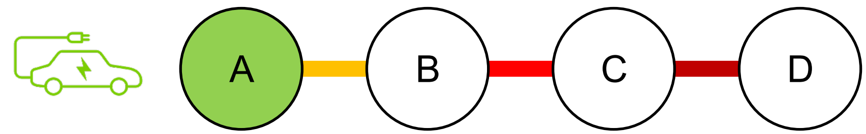

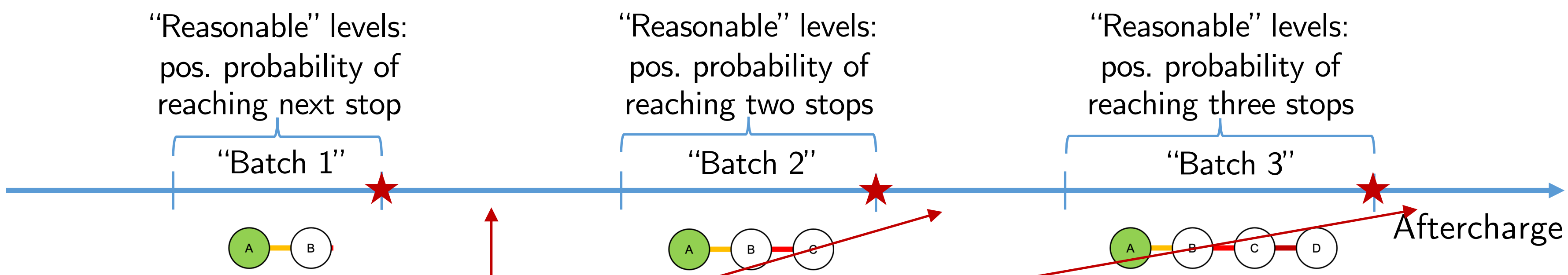

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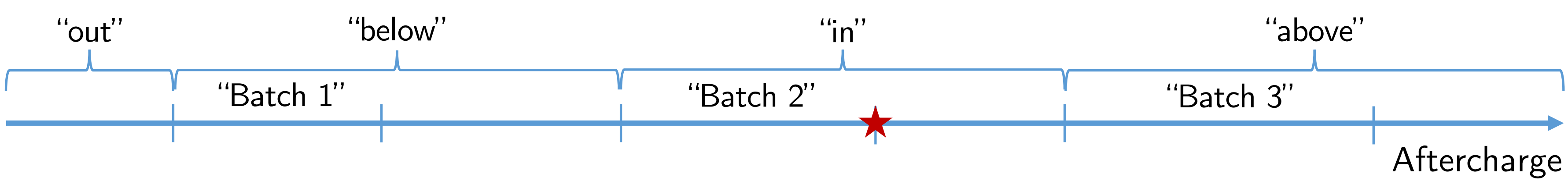
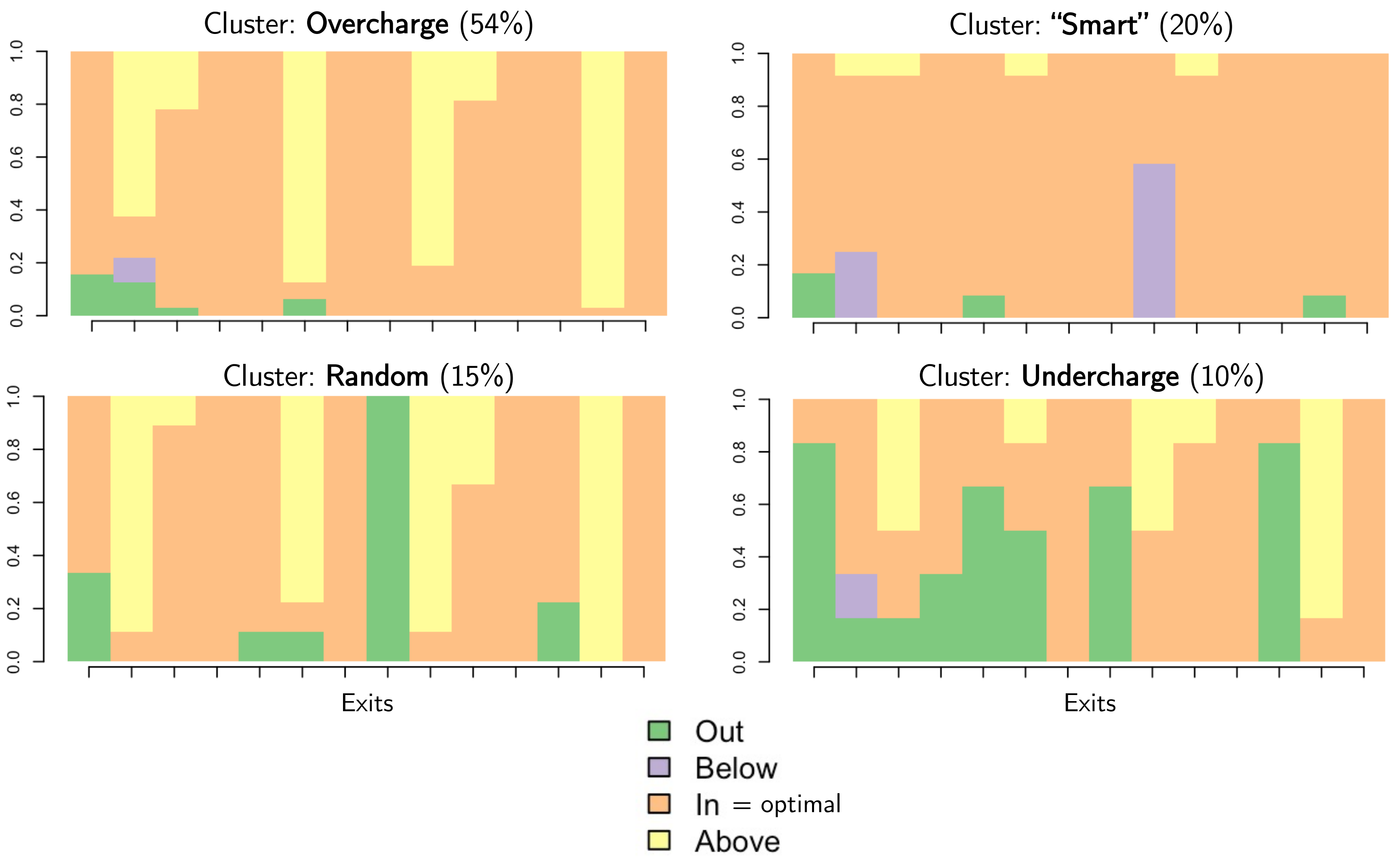


→ Consistent choice of intervals as an indicator of strategic behavior

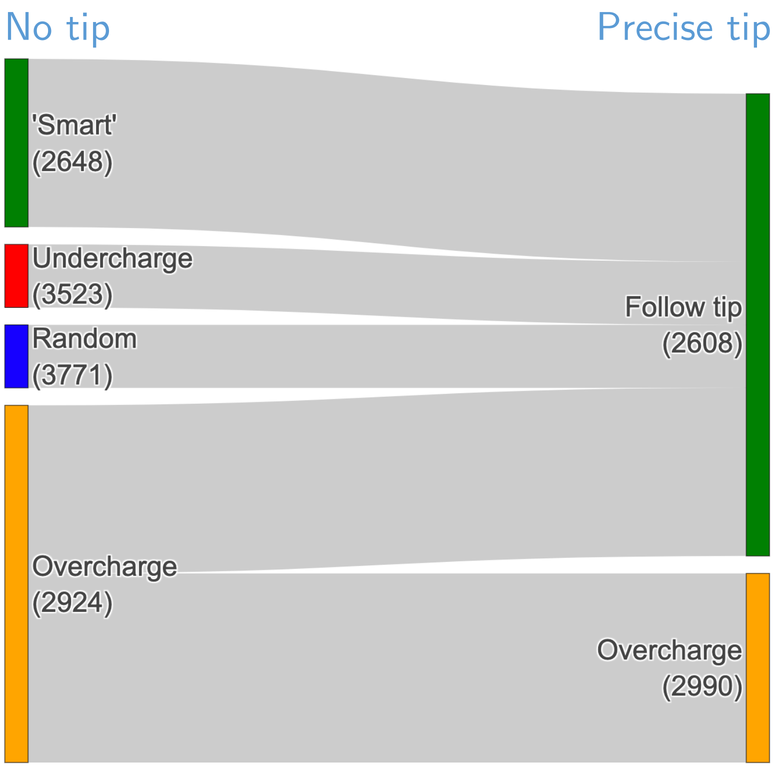
Study 2A:

Results Clustering Pre-Tip Behaviors



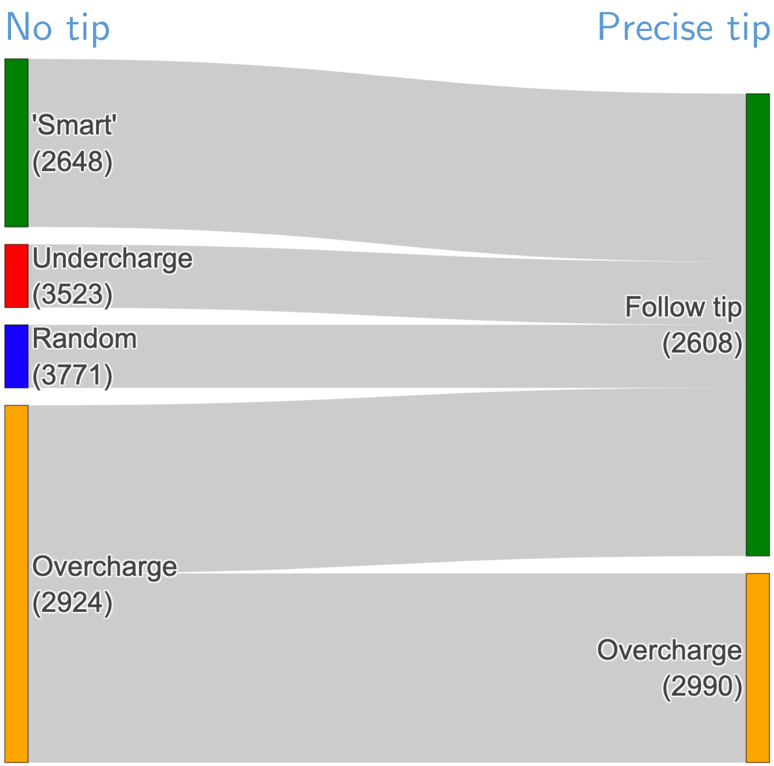
Study 2A:

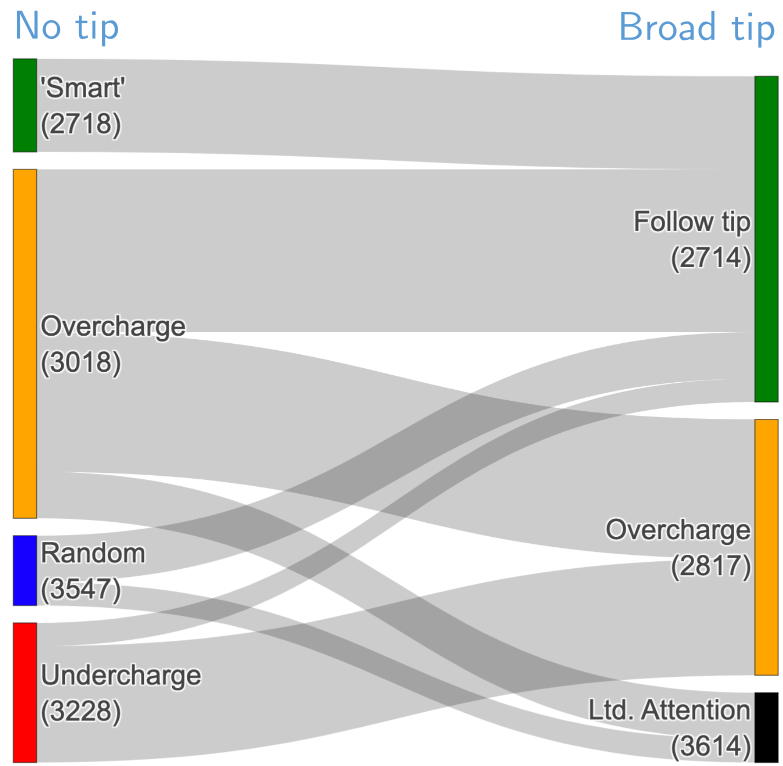
Results Predicting Response to Tip



Study 2A:

Results Predicting Response to Tip



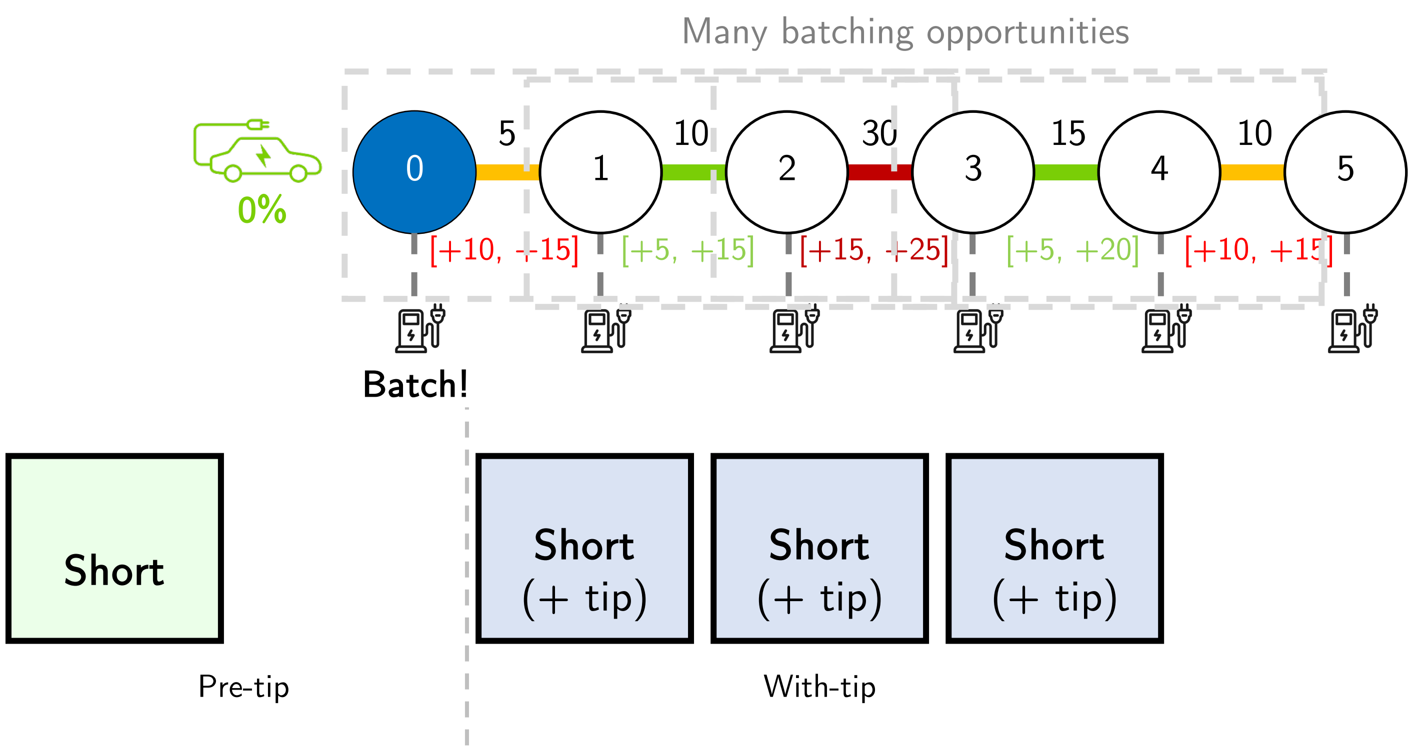


But Did We Help Them Improve Their Decision-Making?

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

Study 2B:

Design Short Map



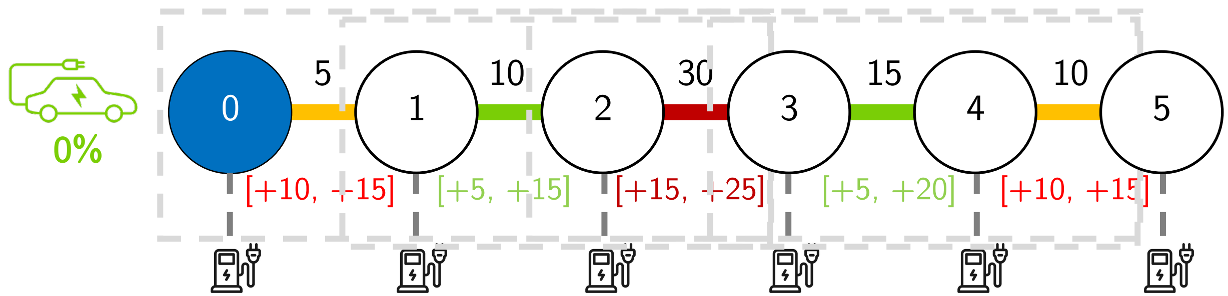
Pre-registered at https://aspredicted.org/7LP_J9G

Study 2B:

Design

Short Map

Many batching opportunities



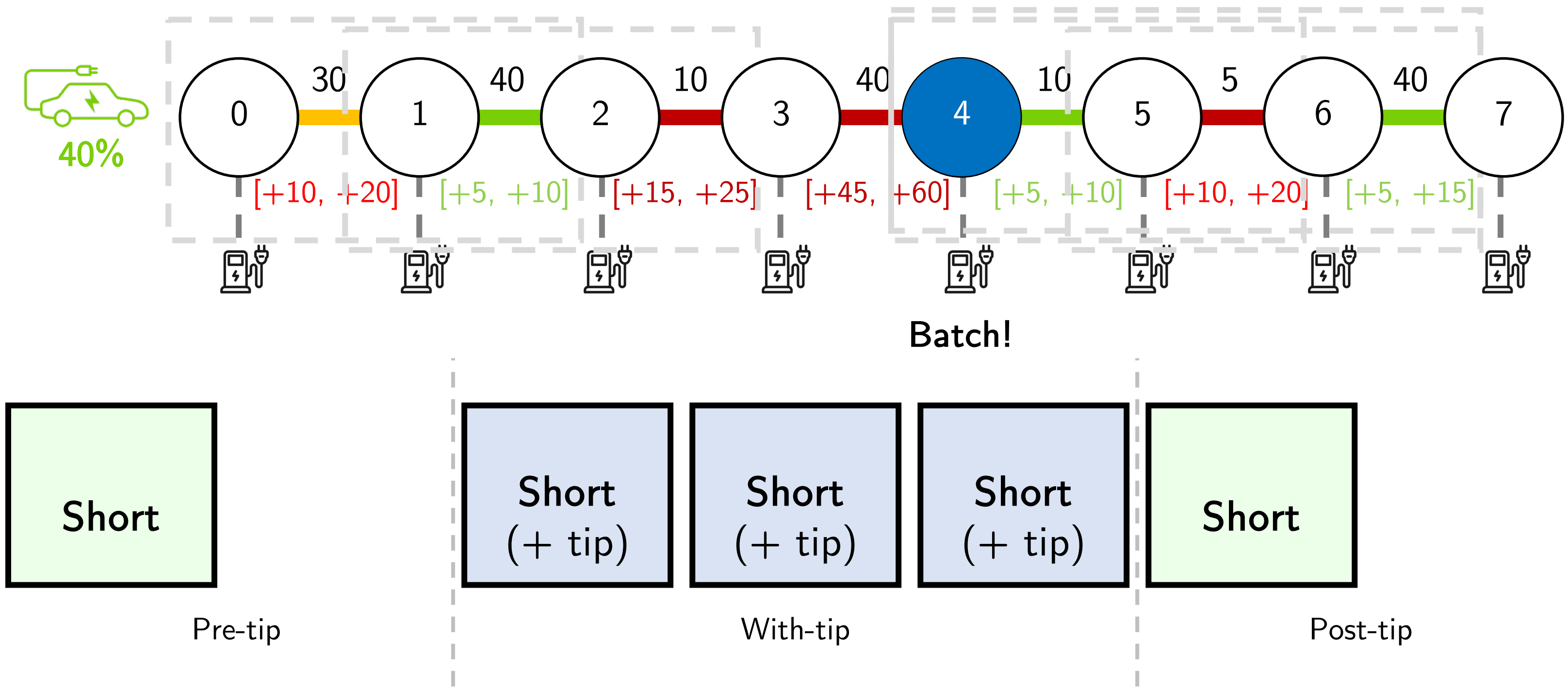
Batch!

Pre-tip	With-tip			Post-tip
Short	Short (+ tip)	Short (+ tip)	Short (+ tip)	Short

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

Study 2B:

Design + Long Map (New Environment)



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

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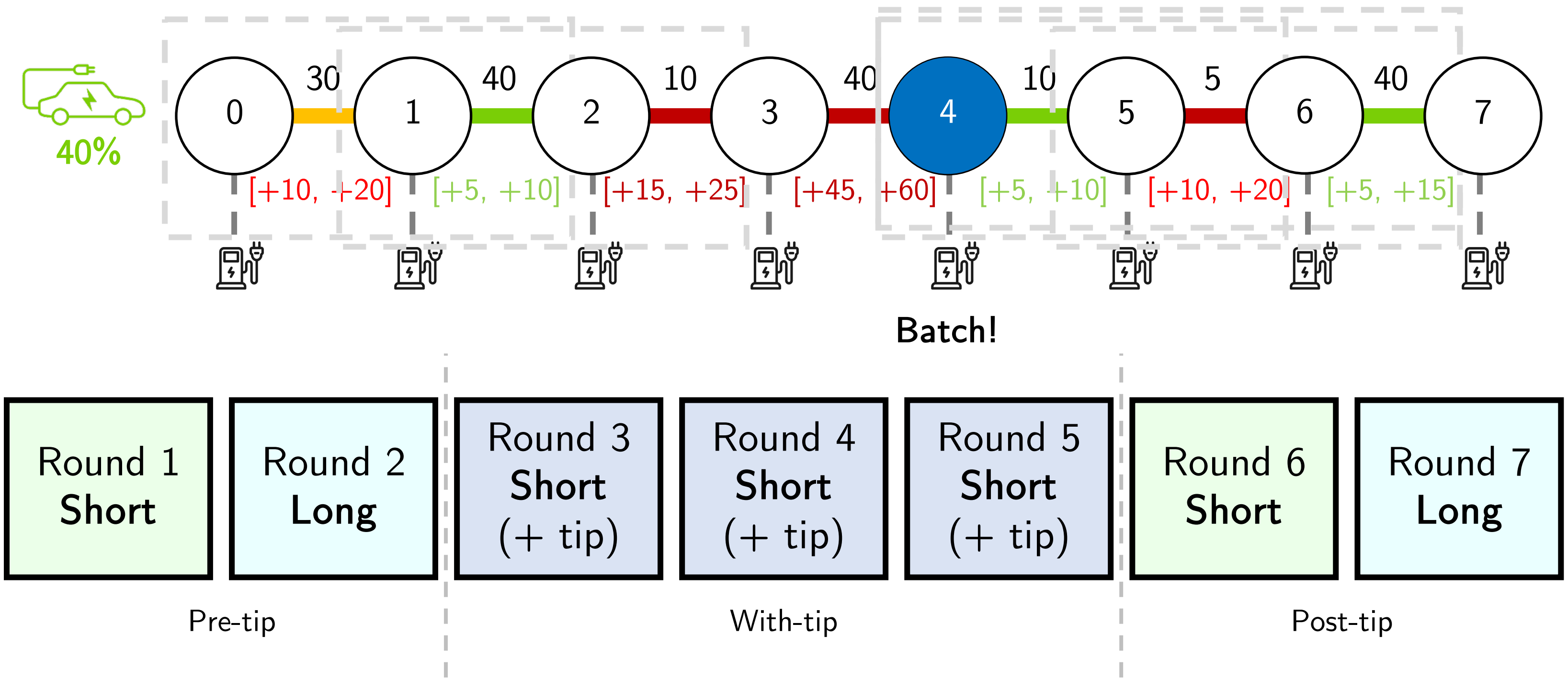

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Study 2B:

Design

2 x 2

tip precision x centered / skewed realized traffic

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

Study 2B:

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**

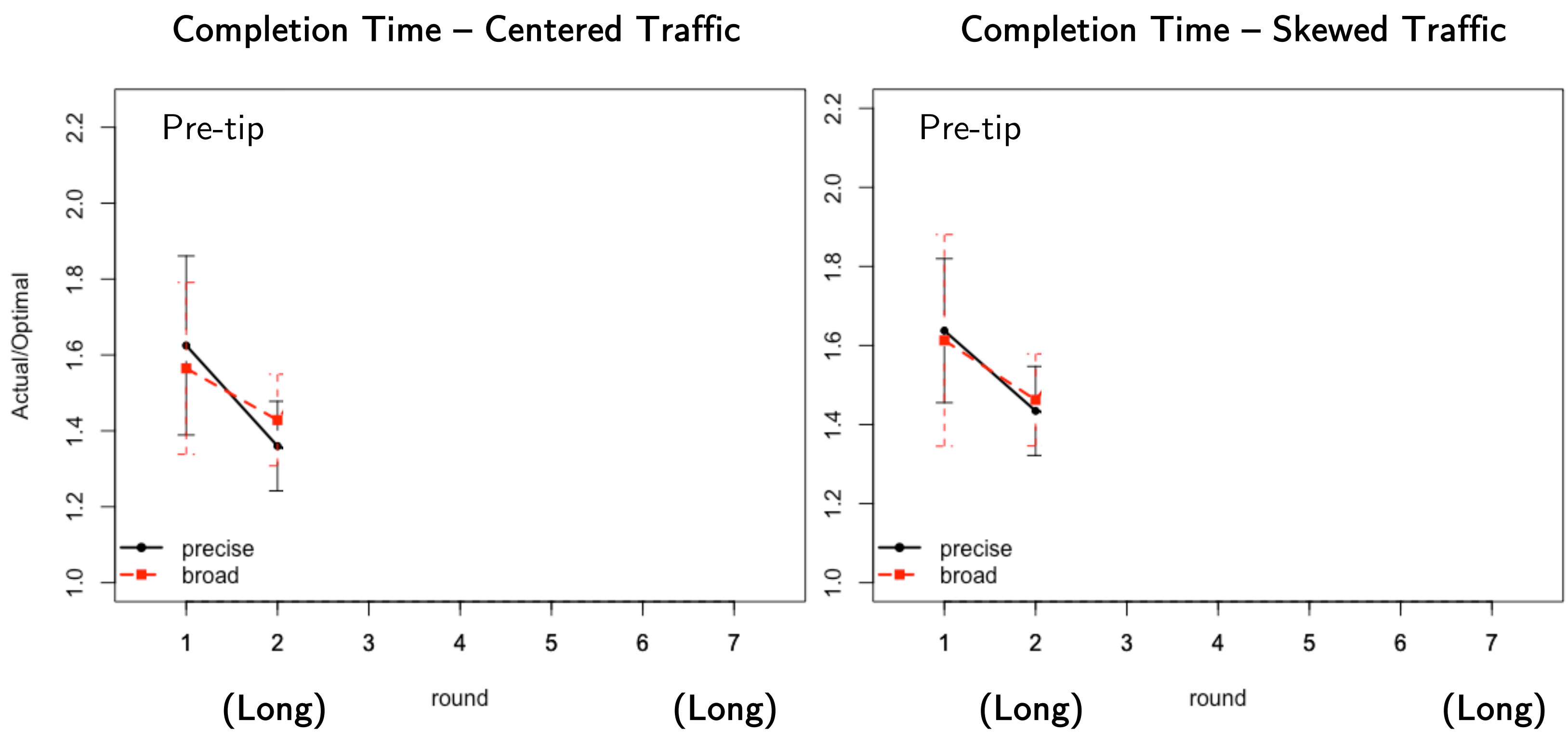
Pre-tip

With-tip

Post-tip

Study 2B:

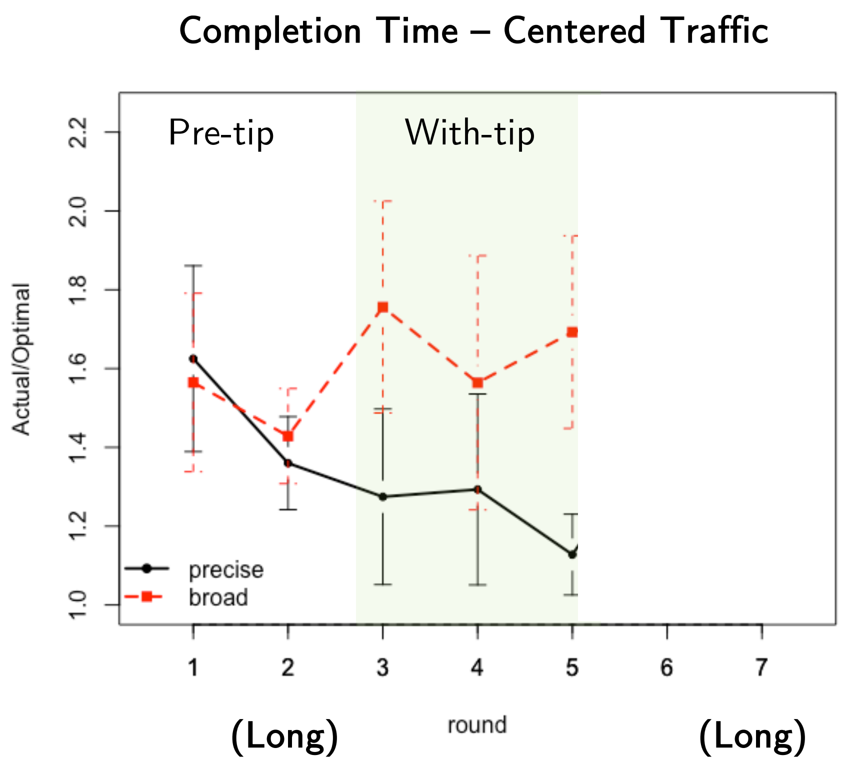
Results Performance Across Rounds

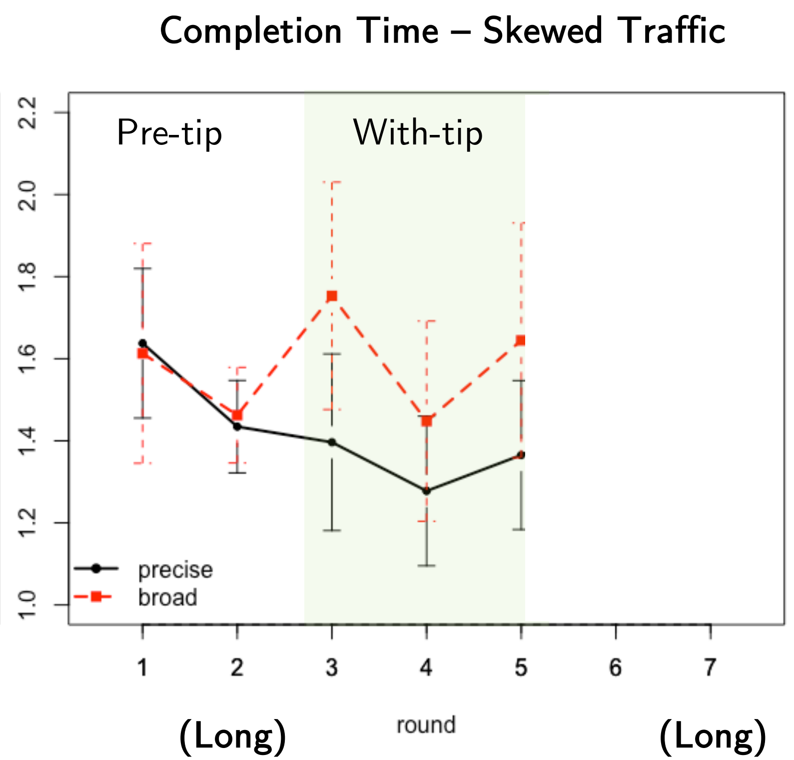


Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2B:

Results

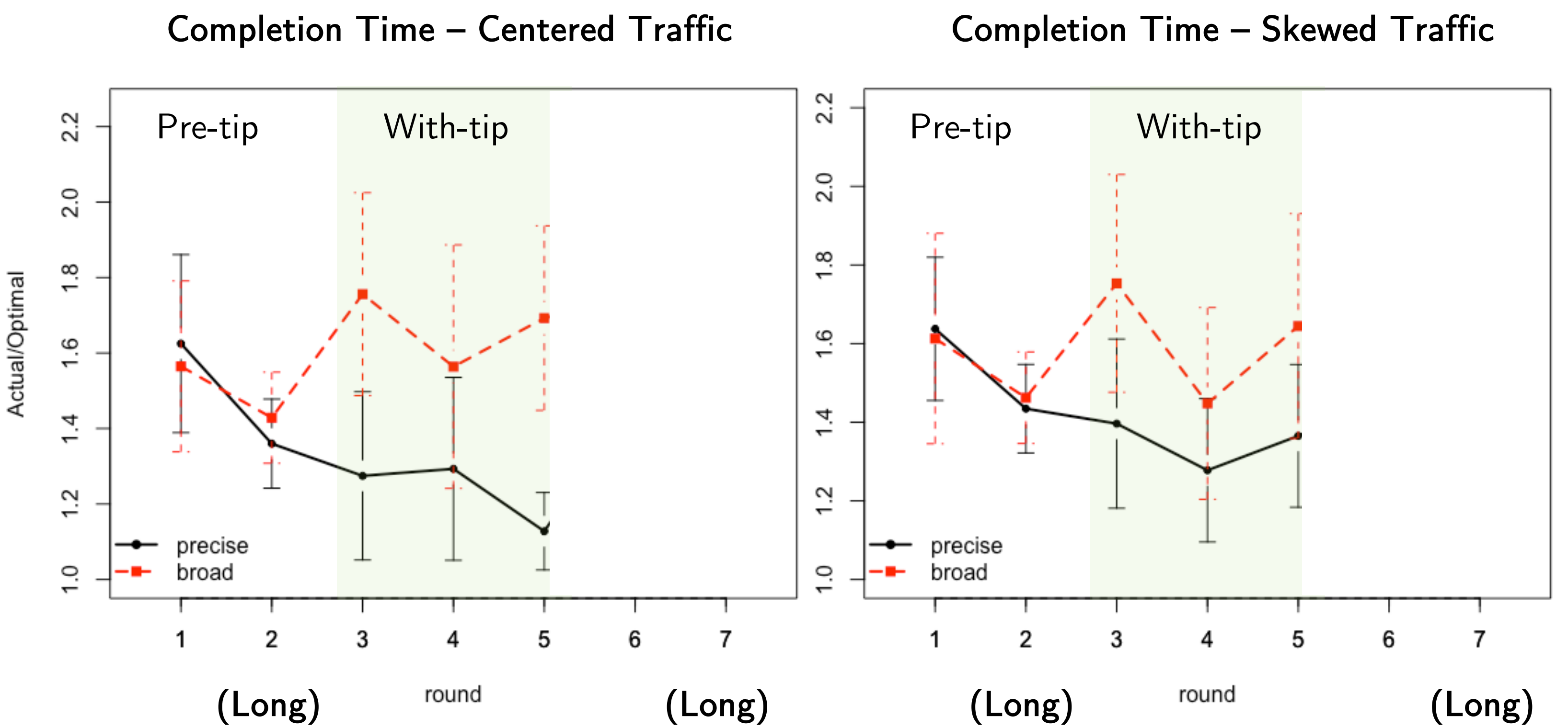




Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2B:

Results Precise Tip Worked, Again



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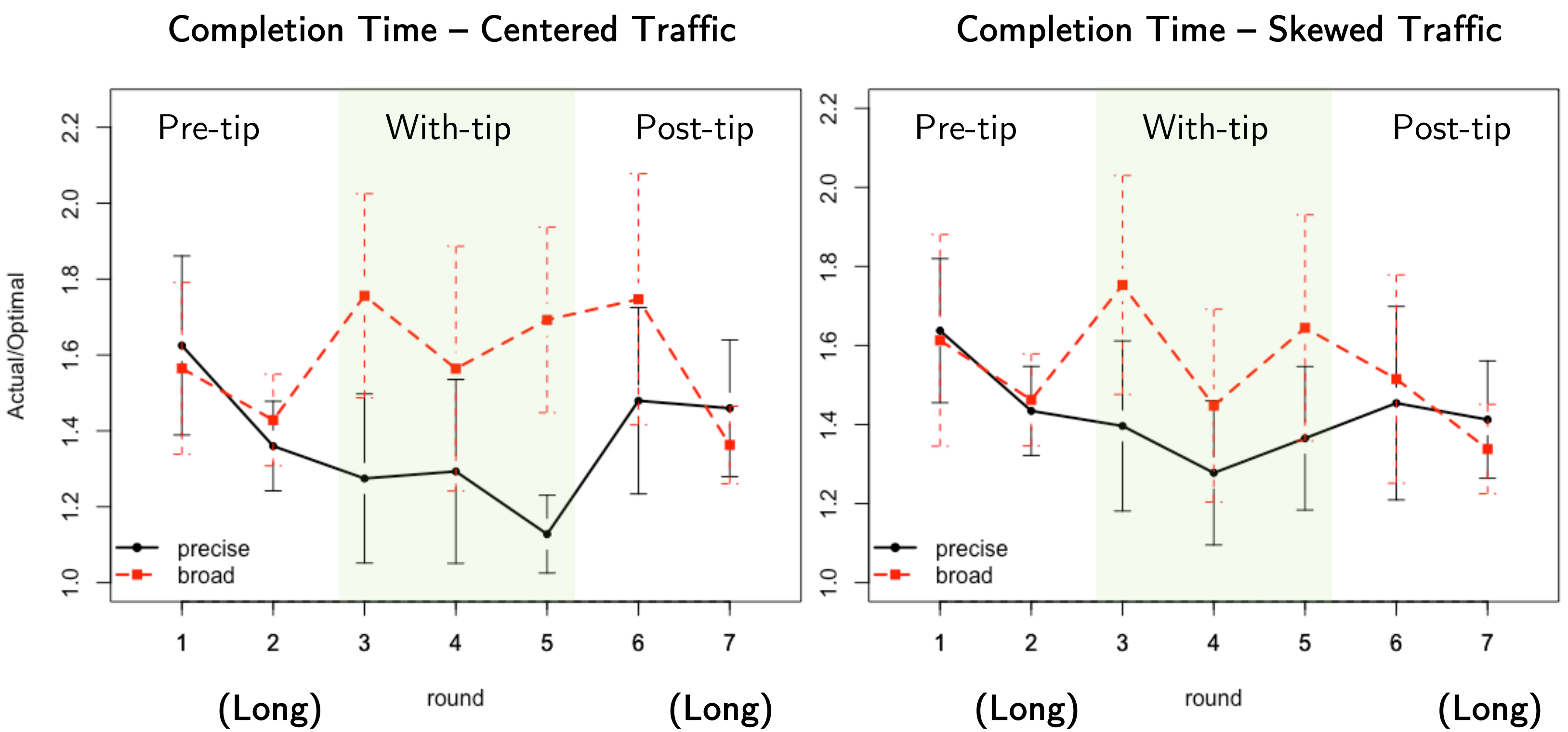
Study 2B:

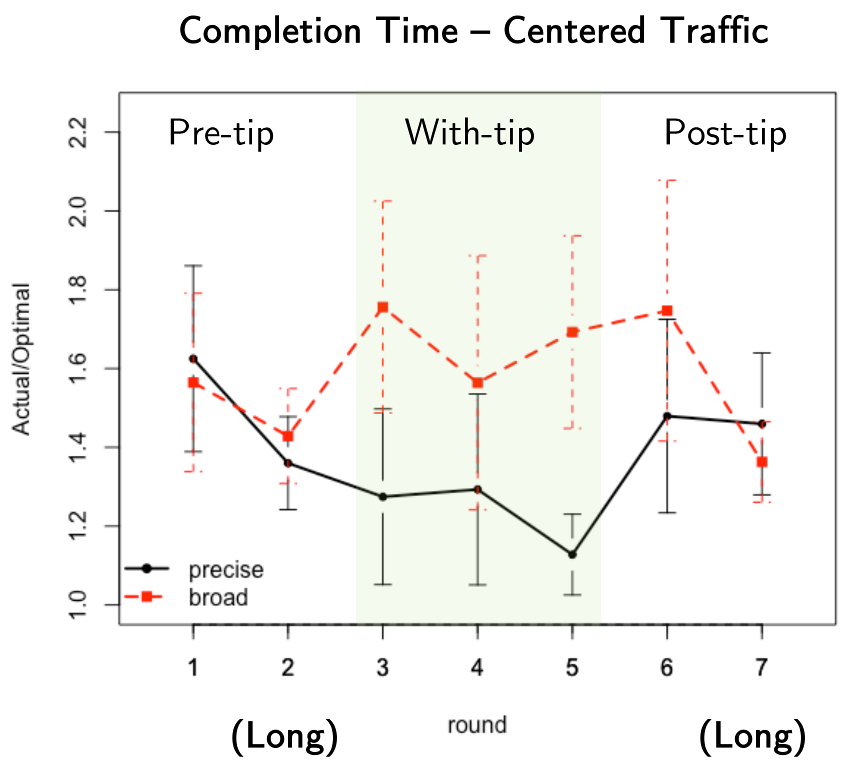
Results

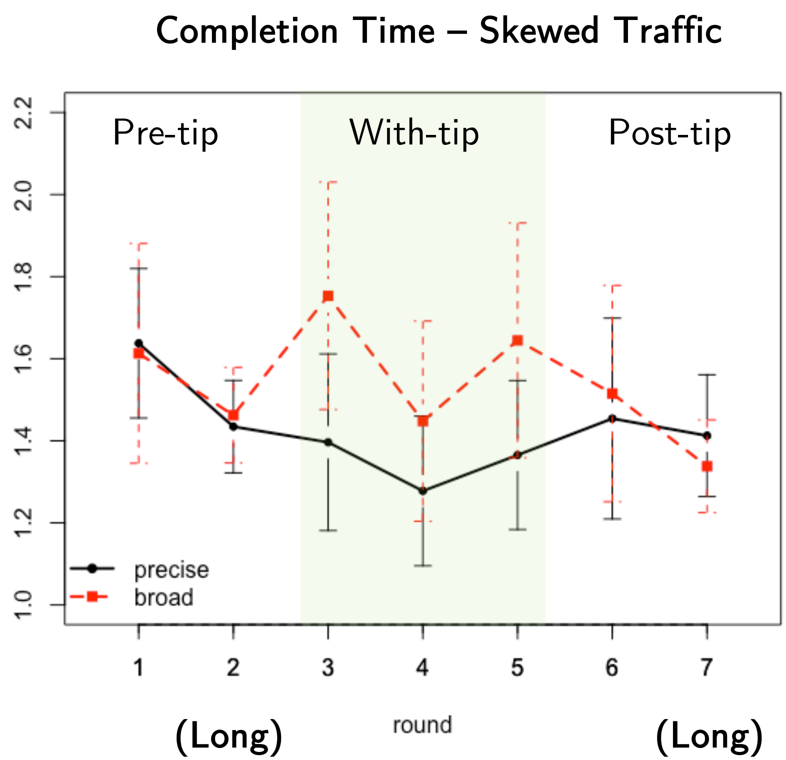


Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 2B:

Results Broad Tip Seemed to Help with New Environment





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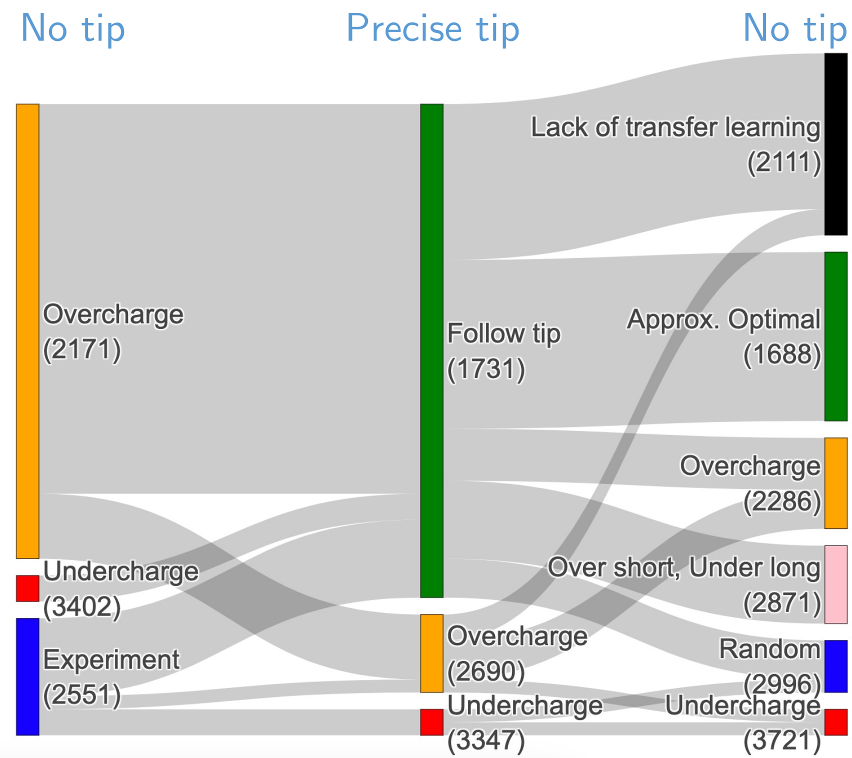
Study 2B:

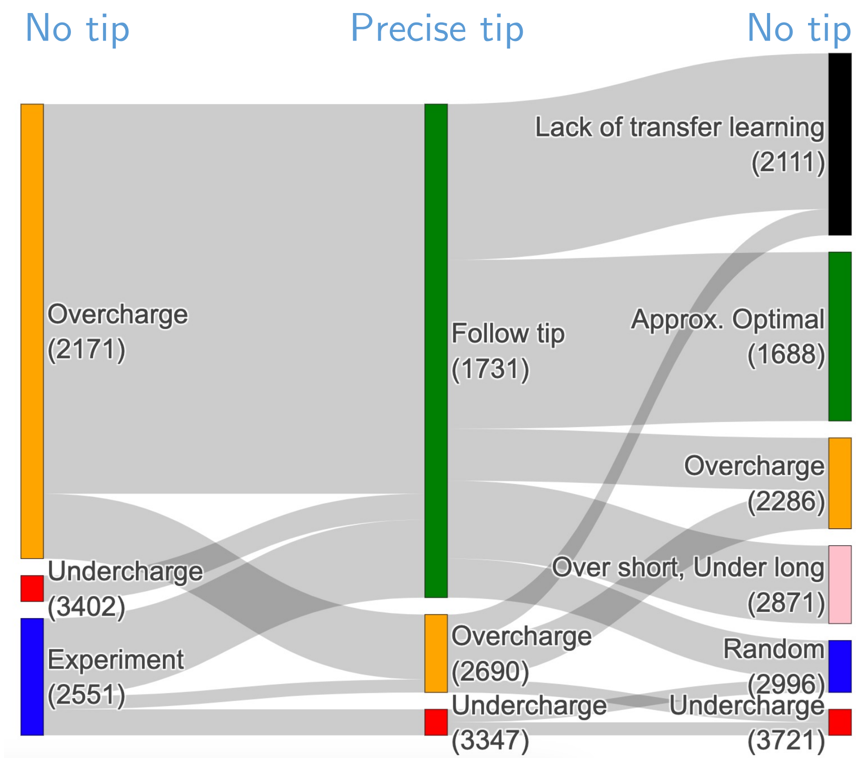
Results Long-Term Learning from Tip



34% stay with
optimal strategy afterwards

Study 2B:

Results Long-Term Learning from Tip



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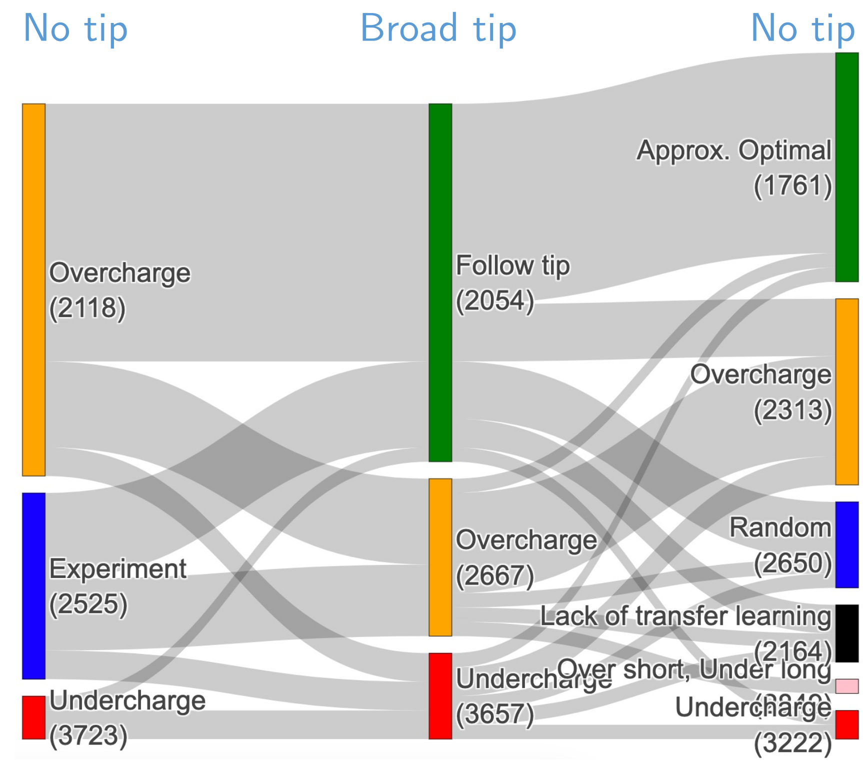
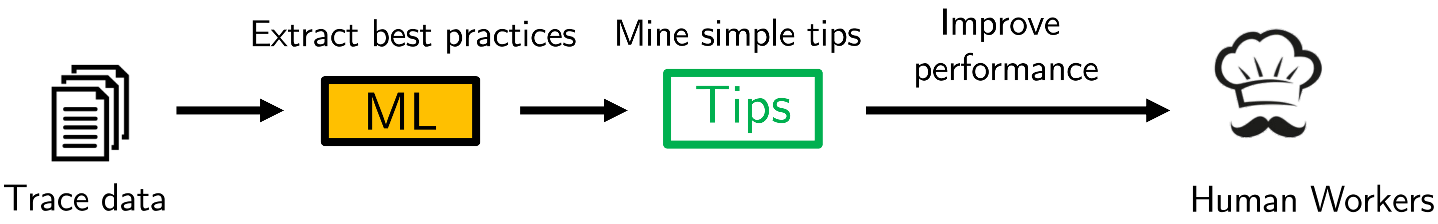


56% stay with
optimal strategy afterwards

Summary

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



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
Major Revision @ Management Science

(Available at: bit.ly/tipspaper)

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

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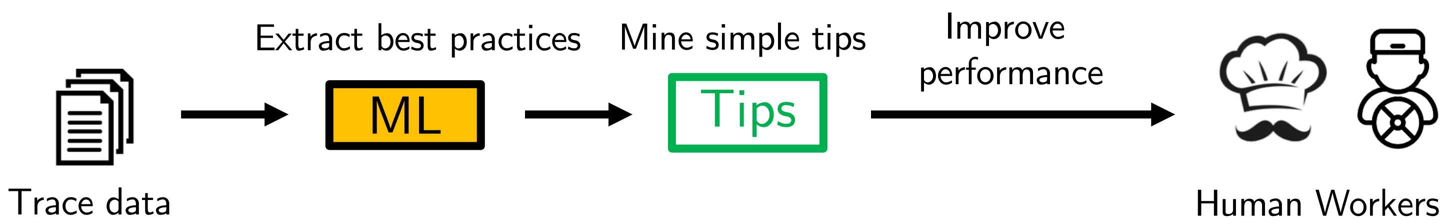

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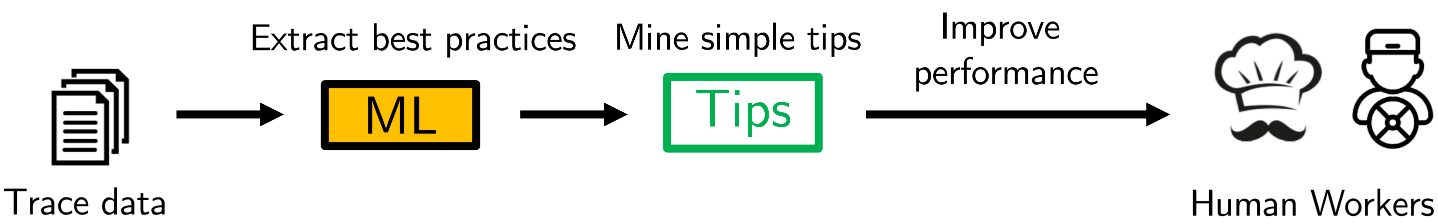

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Thank you! Feedback (+ tips) very welcome!

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Research Overview

1 Operations for the Future of Work

Gig Workers' Decision-Making

- Behavioral & economic drivers on workers' labor decisions/scheduling
  (with Gad Allon, Maxime Cohen, MSOM 2023)
- Multihoming, incentive schemes
  (with Gad Allon, Maxime Cohen, Ken Moon, working paper)

Gig Workers' Learning

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

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2 Human-AI Interfaces in Operations

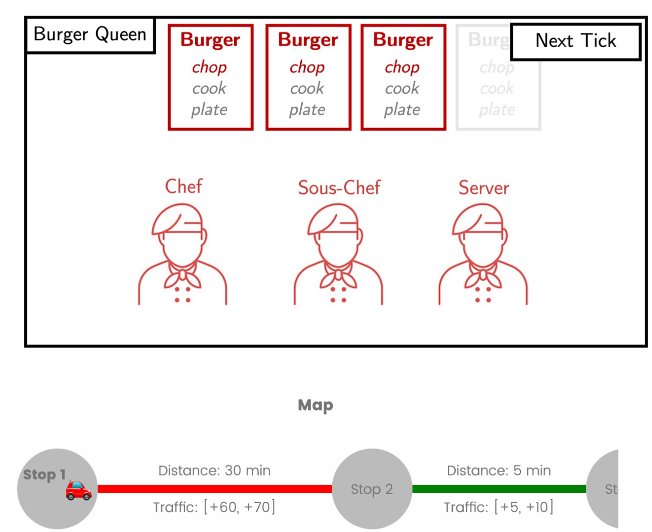
Tips for Sequential Decision-Making

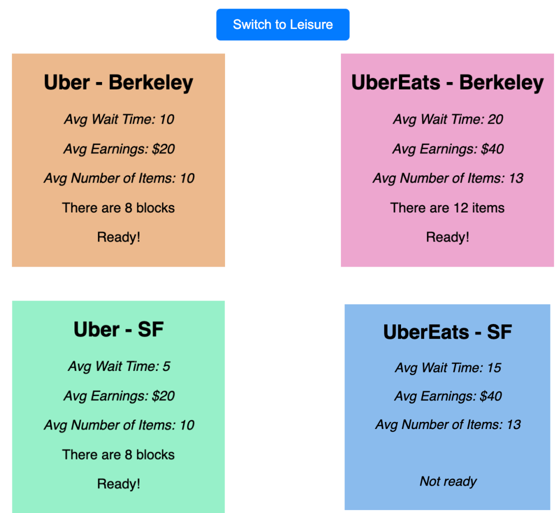
- Learning best practices from data and mining simple advice
  (with Hamsa Bastani, Osbert Bastani, Major Revision at Management Science)
- Uncertain environment, precision of machine-generated advice
  (with Philippe Blaettchen, work in progress)
- Characterizing non-adoption
  (with David Lee, work in progress)
- Education: teachers' planning
  (with Sam Keppler, Clare Snyder, work in progress)
- Pricing competing products
  (with Olivia Natan, work in progress)

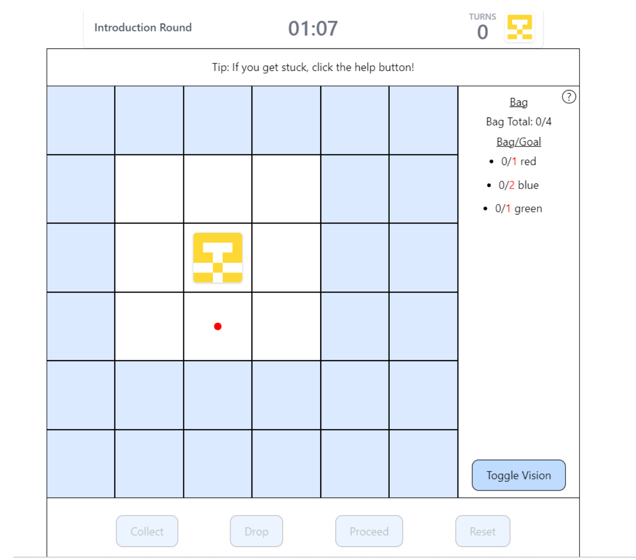
Research Overview

Berkeley Operations & Behavioral Analytics Lab

Develop decision-making games to study humans decision-making/learning and design algorithms to help them improve







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Results Learning Beyond Tips

Sous-Chef
chops 3 times

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

Results Learning Beyond Tips

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

Sous-Chef
chops 3 times

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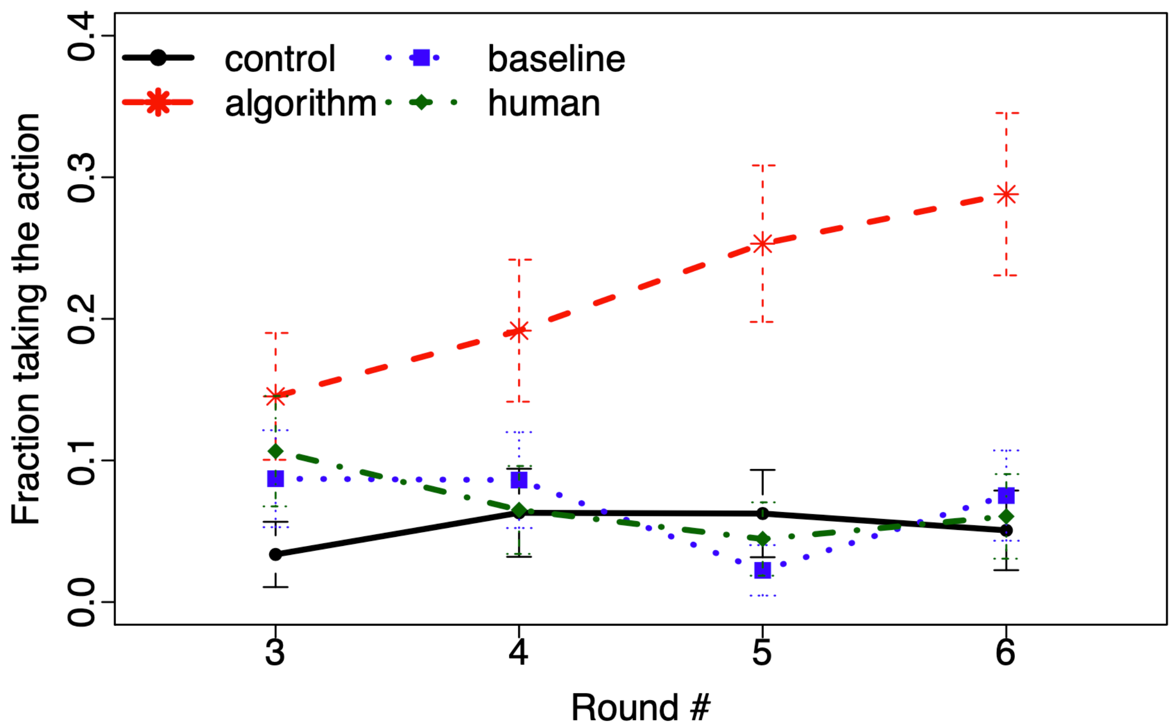
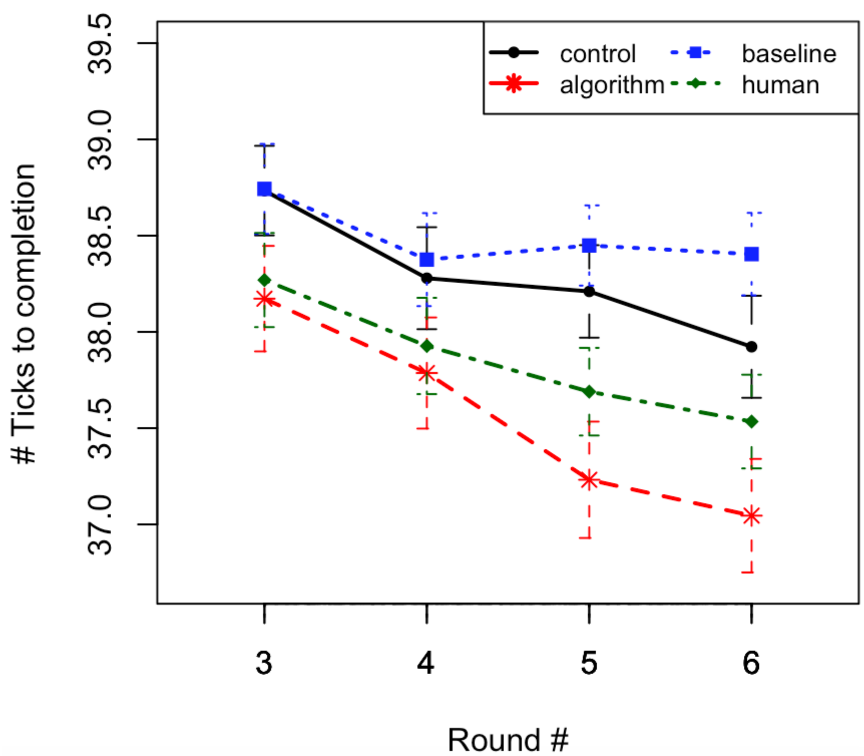


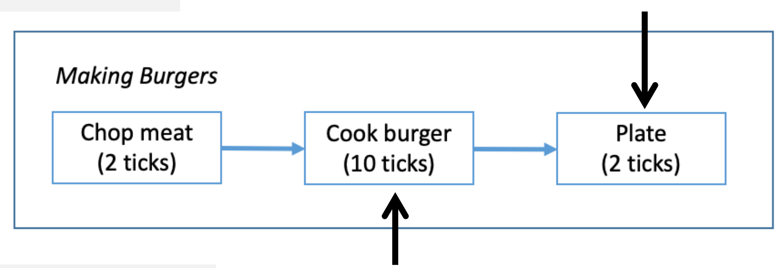
Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

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

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.

Additional Results

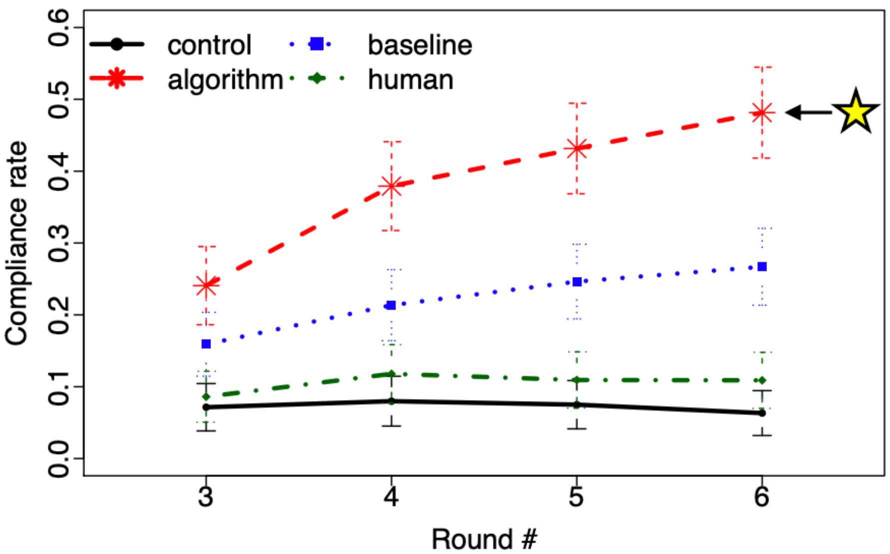
	Phase I: Normal	Phase II: Normal	Phase I: Disrupted	Phase II: Disrupted
Total	183	1,317	172	1,011
Mean age [range]	34.6 [18, 76]	33.3 [18, 74]	34 [19, 76]	34.9 [16, 84]
Female	57.38%	51.03%	61.63%	60.14%
$\geq$ 2-year degree	73.22%	67.73%	77.91%	70.43%
Median duration	18.82 minutes	20.50 min	27.80 min	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	Baseline	Human
	"Chef shouldn't plate"	*"Chef chops once"*	*"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%

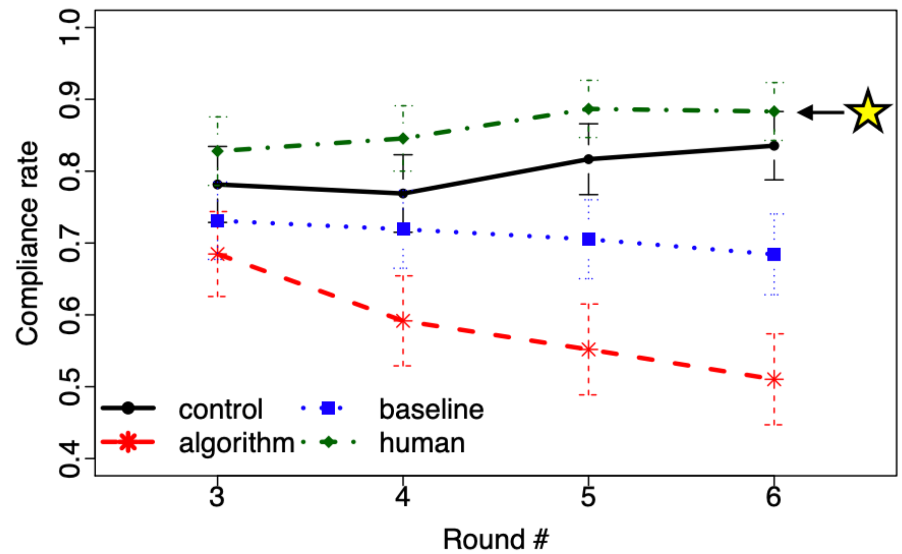
Table 7: Participants' coded feedback on the provided tips (normal configuration).

Disrupted	Algorithm	Baseline	Human
	"Server cooks twice"	*"Sous-chef plates twice"*	*"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%

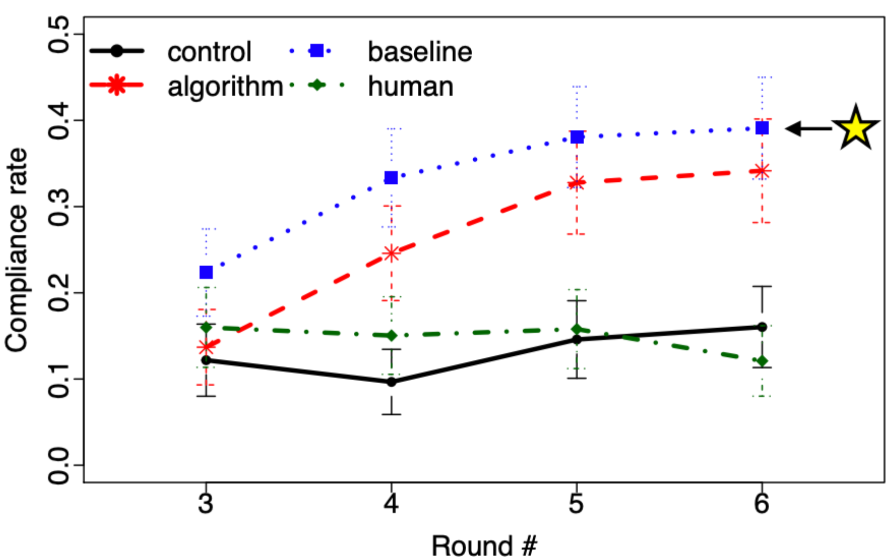
Table 8: Participants' coded feedback on the provided tips (disrupted configuration).



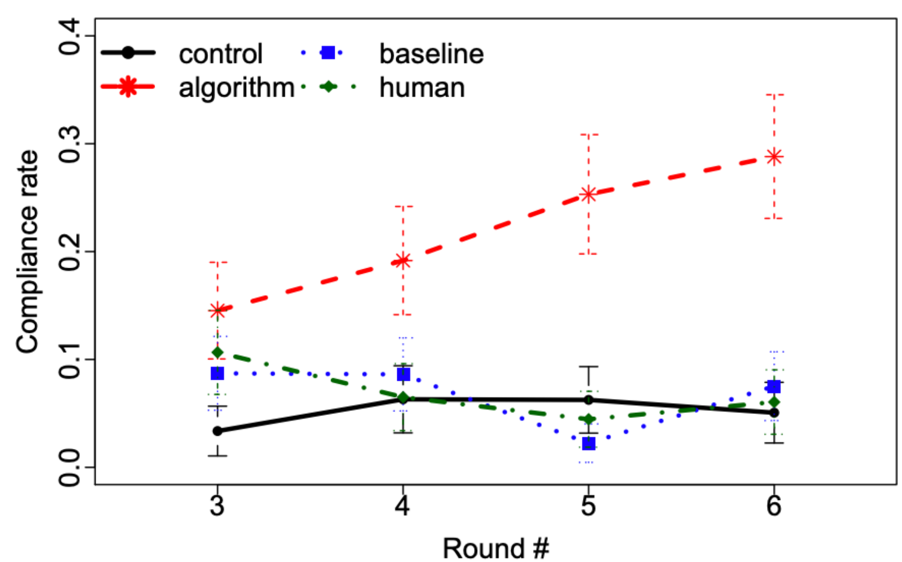
(a) Algorithm Tip: "Server cooks twice"



(b) Human Tip: "Server cooks once"

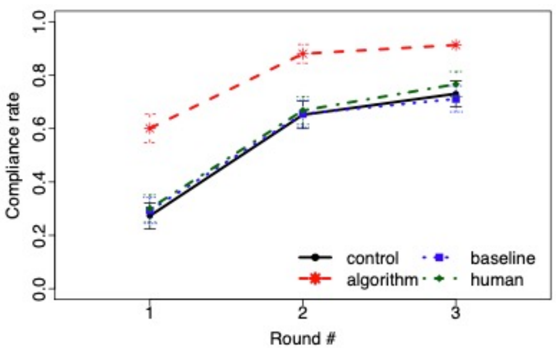


(c) Baseline Tip: "Sous-chef plates twice"



(d) Unshown Tip: "Server chops once"

Learning Beyond Tips



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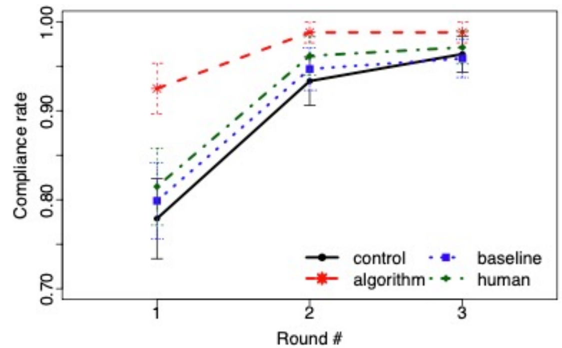
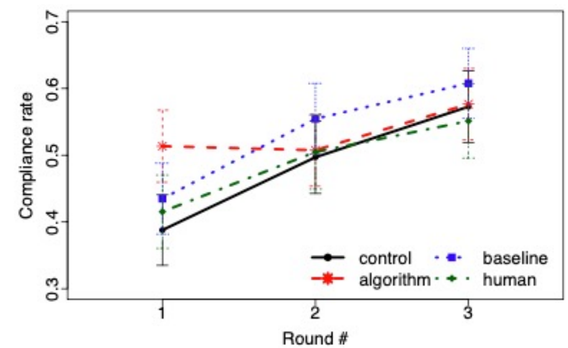
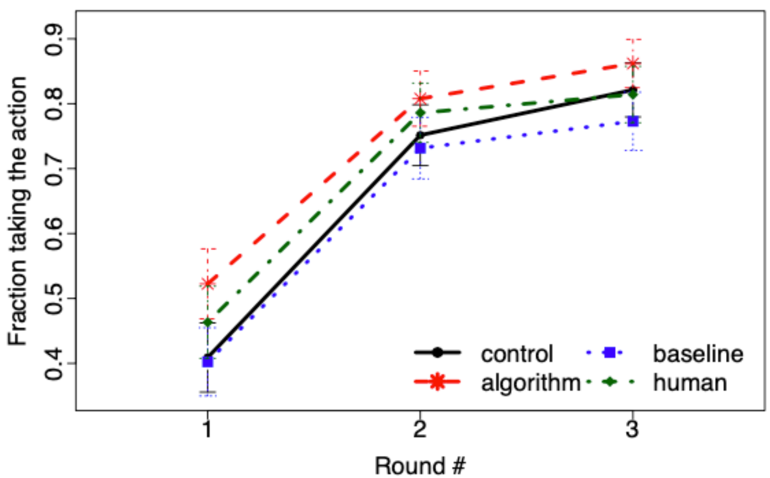


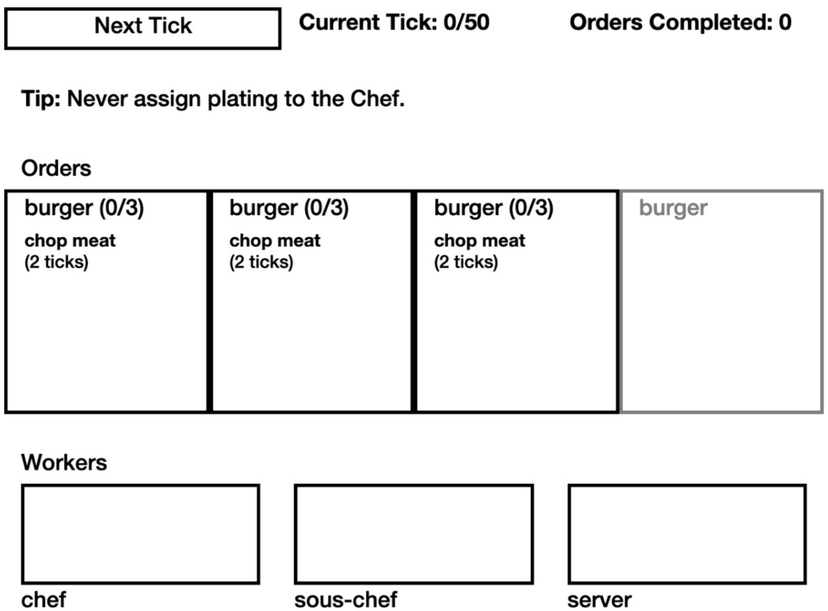
(b) Human: "Leave some idle"



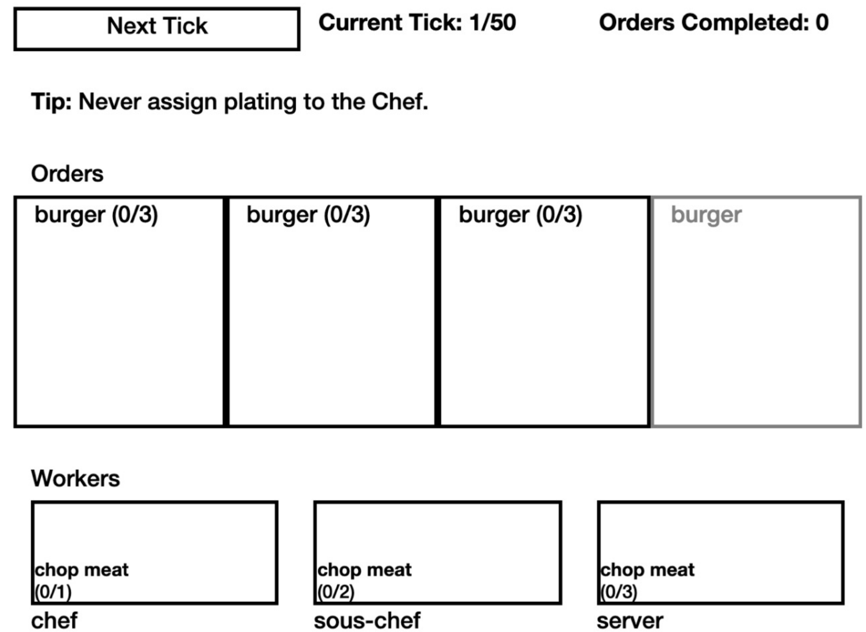
(c) Baseline: "Chef chops once"



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



(a) The initial state where users observe available subtasks, median times to completion, and three idle virtual workers. The interface also shows the current tick, time limit, current progress, and potential tip.



(b) The next state after all three previously available subtasks were assigned to the virtual workers and the true completion times were realized, revealing different levels of virtual workers' skills.