

Improving Human Decision-Making with Machine Learning

Park Sinchaisri
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

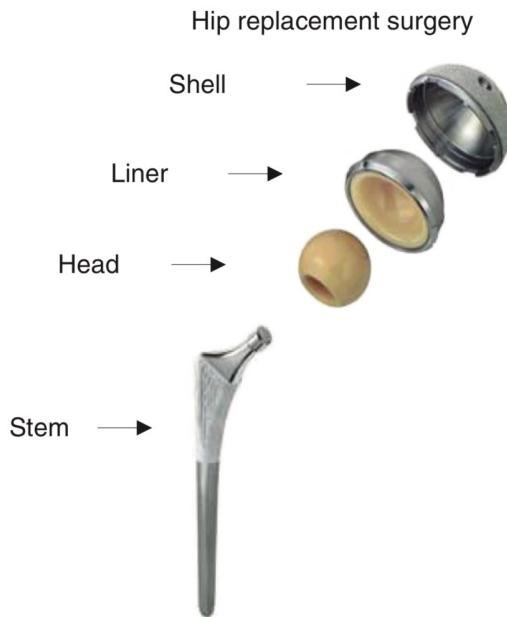
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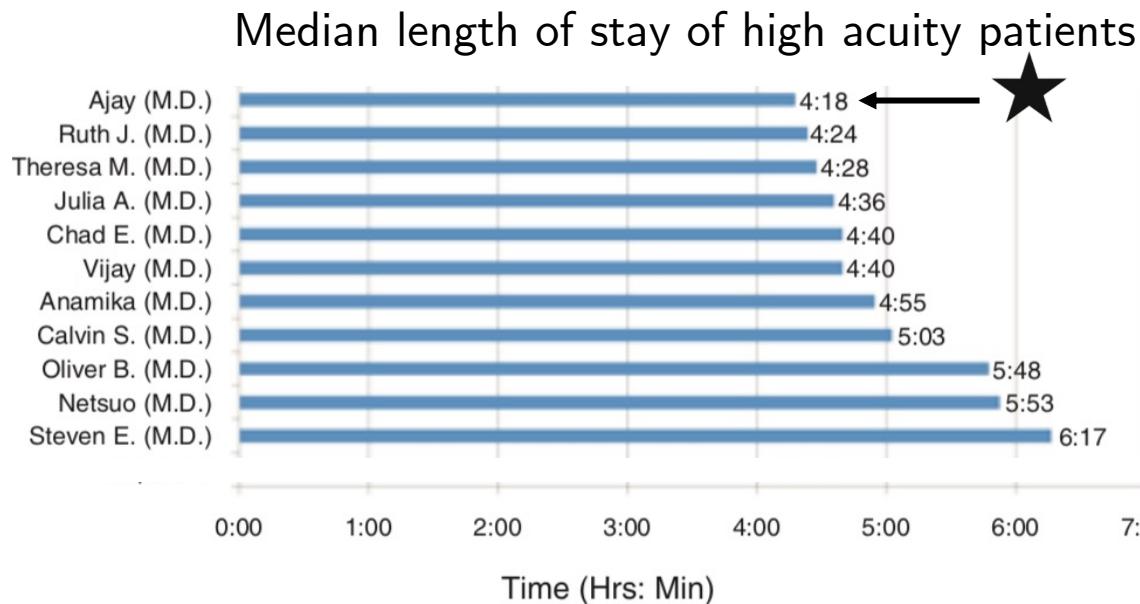
New device = **+32.4%**
surgery duration

- Ramdas et al. 2018

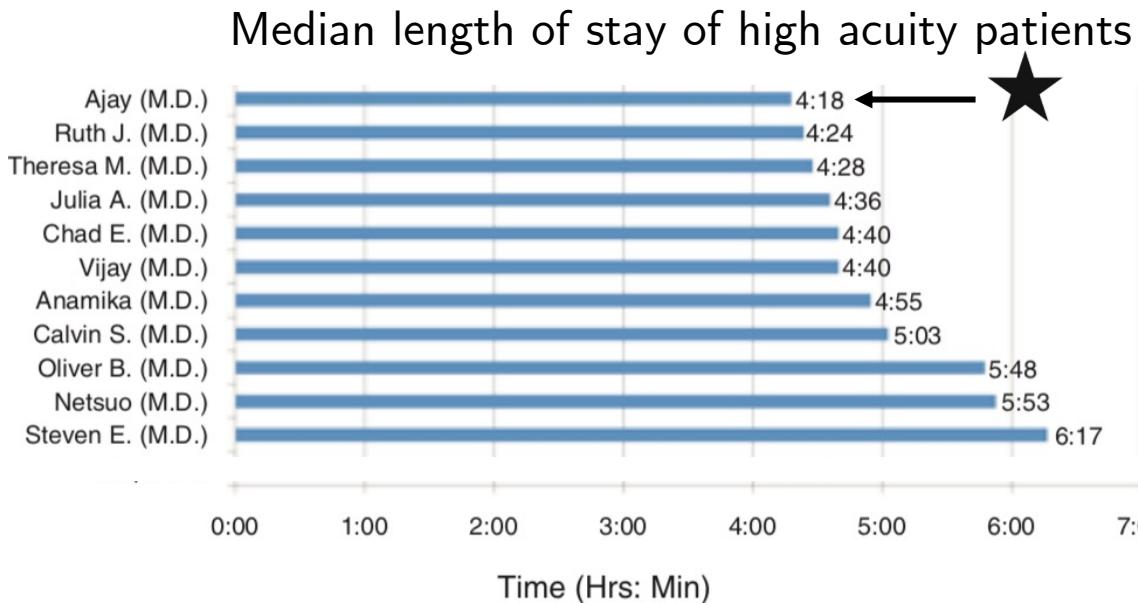
Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019,
Bavafa & Jonasson 2020, Bloom et al 2020, ...

Learning from Experts

Learning from Experts



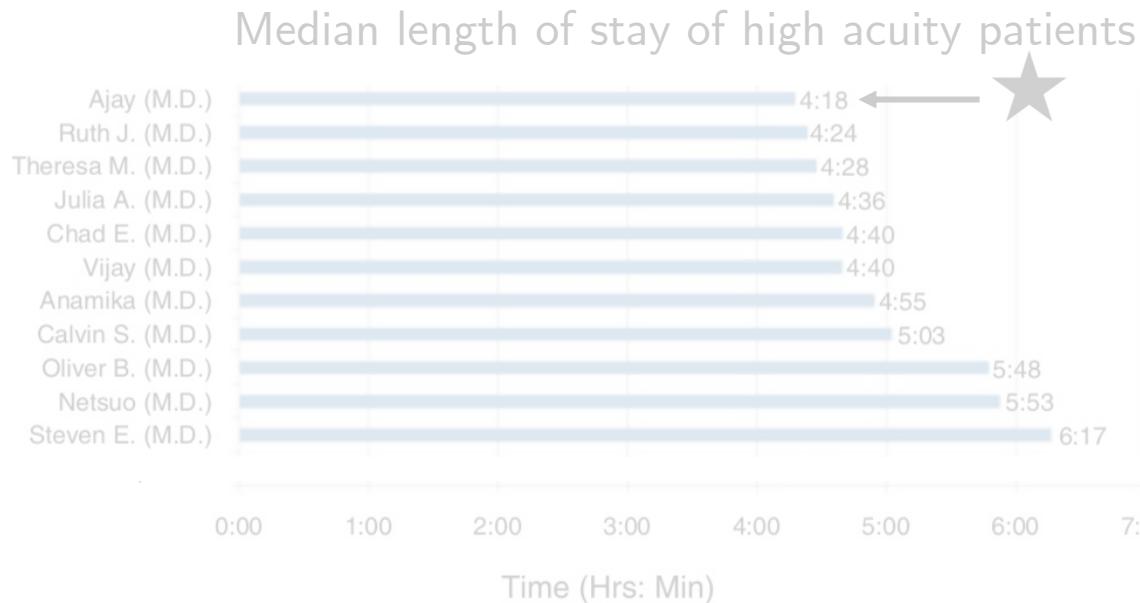
Learning from Experts



+10.9%
productivity
- Song et al. 2018

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

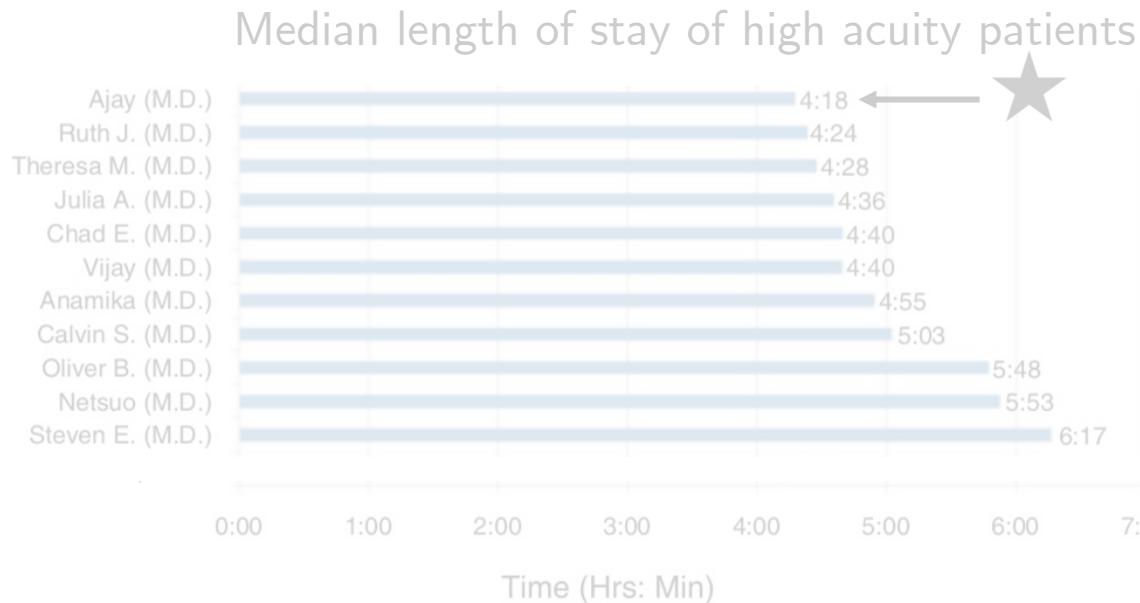
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Learning from Experts



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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
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KLECK,MICHAEL	Office Visit - Abbreviated		JONES,CAMERON,MD reviewed by: SUSAN status: Reviewed	05•12•17
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Uber Drivers



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Uber Drivers



Trace data



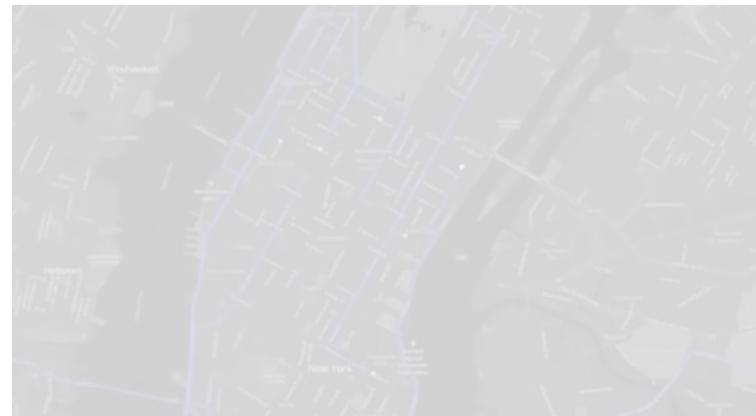
Tips

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Uber Drivers



Extract
best practices



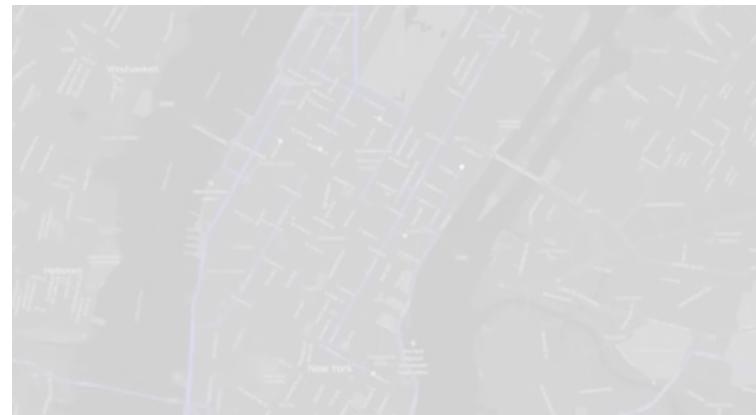
Mine
simple tips

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Uber Drivers



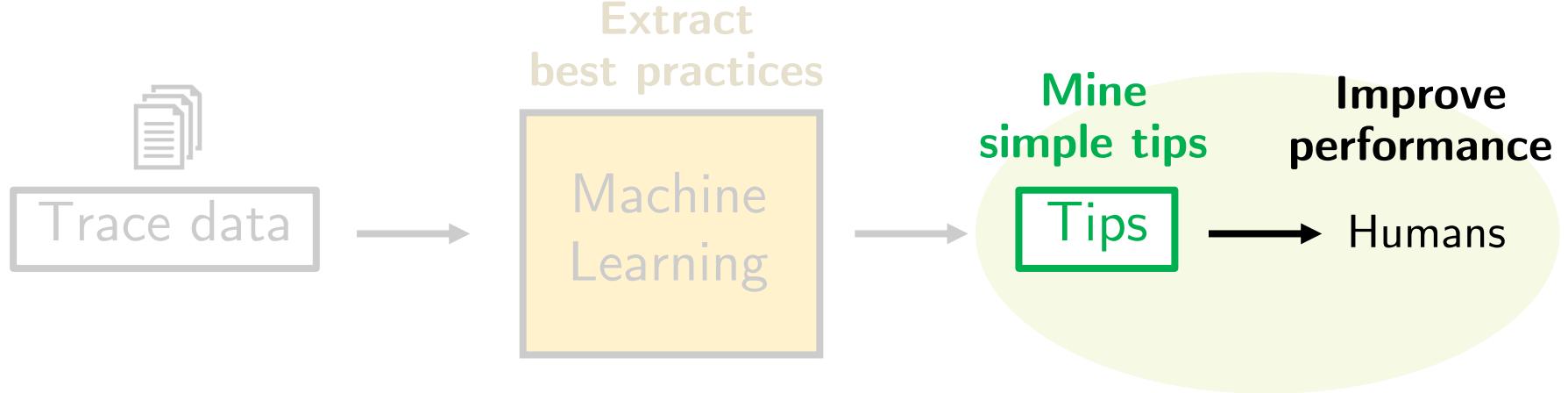
Mine simple tips

Tips

Improve performance

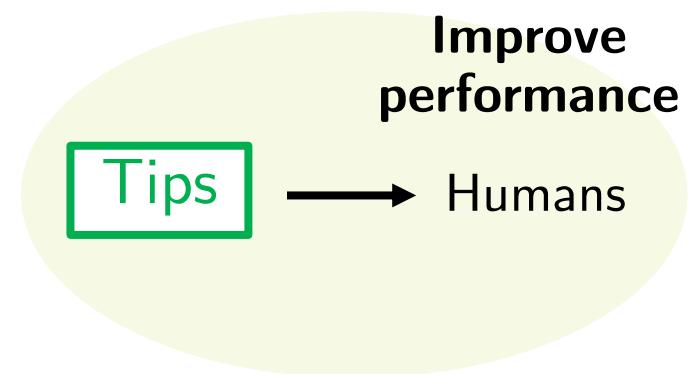
Humans

Potential Issues



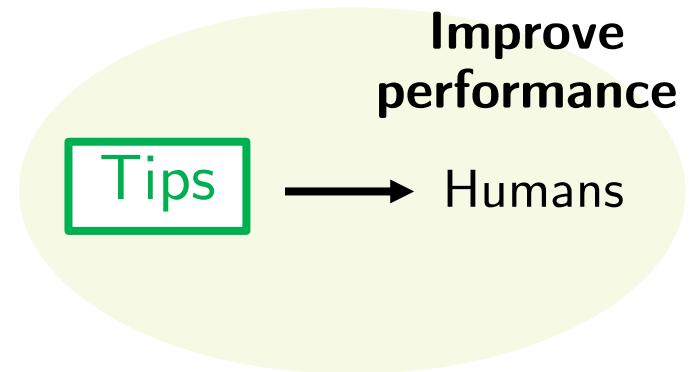
Potential Issues

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



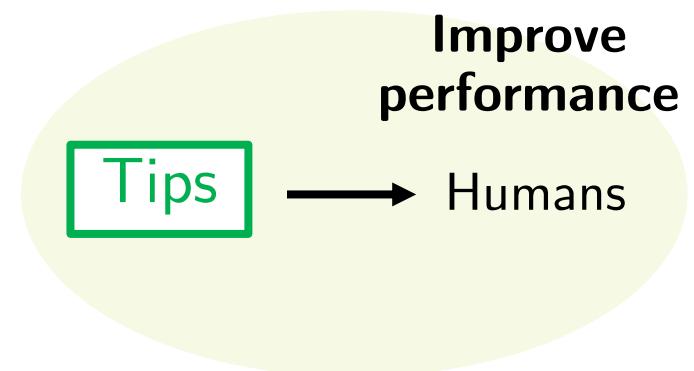
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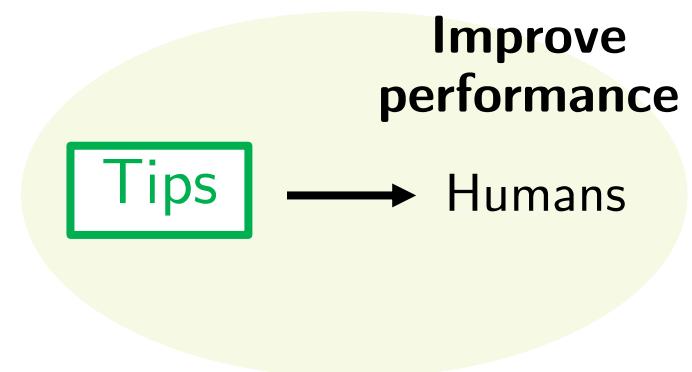
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- Interpretability, inability to precisely implement



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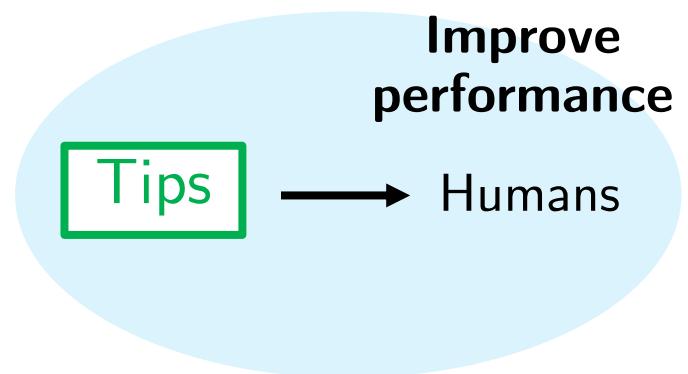
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- Interpretability, inability to precisely implement
- Learning curve, spillovers



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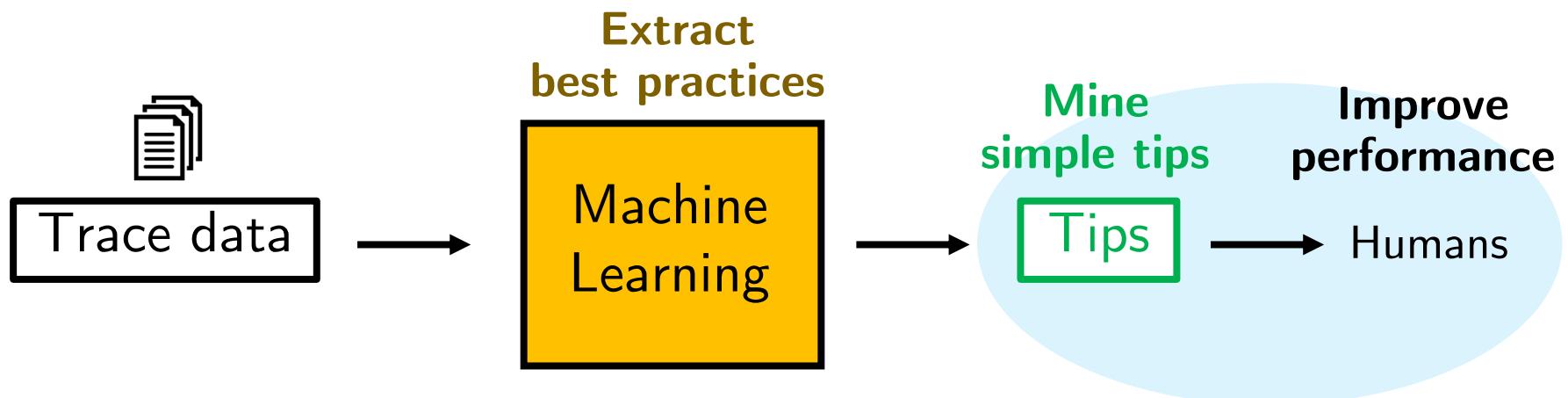
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Controlled environment to
observe human learning
& decision-making



How to Help Humans

Improve Their Decision-Making?



How to Help Humans

Improve Their Decision-Making?

Today:

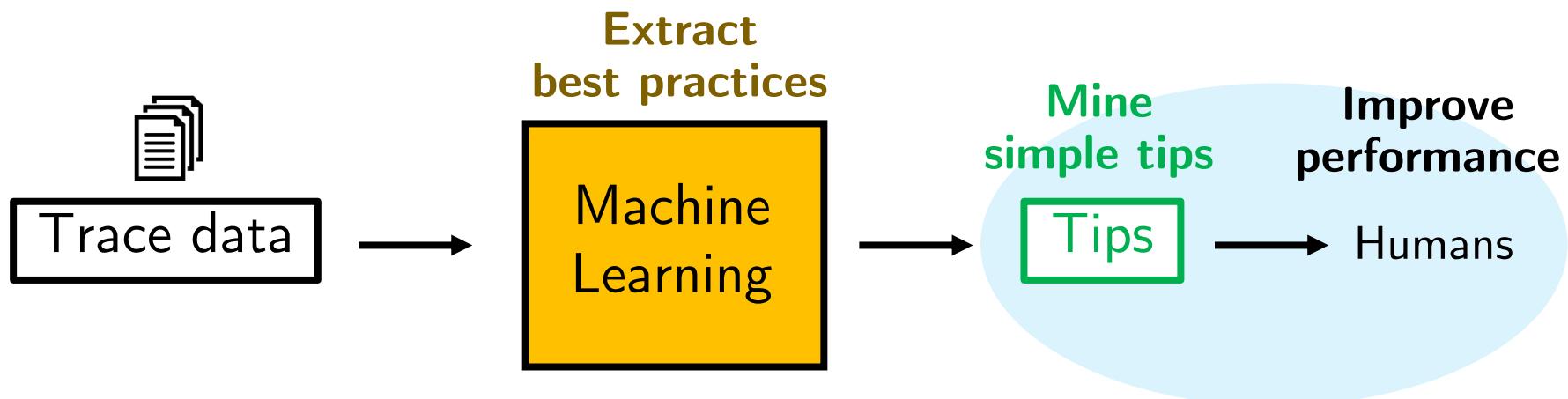
Experimental Design 

Tip Inference

Results: Performance/Compliance

Improving Compliance

with Hamsa Bastani & Osbert Bastani
Major Revision @ Management Science



How to Help Humans

Improve Their Decision-Making?

Today:

Experimental Design 🍔

Tip Inference

Results: Performance/Compliance

Improving Compliance

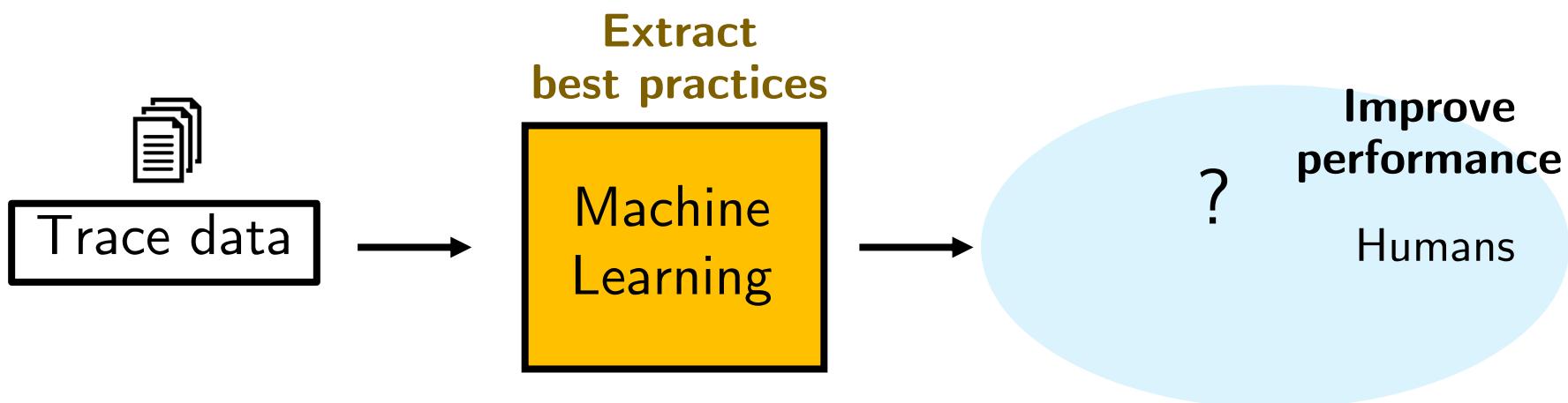
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Experimental Design ⚡

+ Precision of Tips

+ Learning Post-Tip

with Philippe Blaettchen
Work in Progress



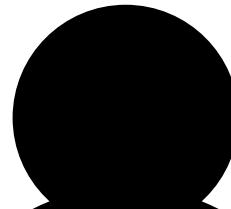
Study 1:

Cooking Game

Burger Queen



x 4 within 50 ticks



Participant

Pre-registered at

<https://aspredicted.org/blind.php?x=8ye5cb>

Study 1:

Cooking Game

Burger Queen



x 4 within 50 ticks

Making a Burger

Chop meat
(2 ticks)

Cook burger
(10 ticks)

Plate
(2 ticks)

Study 1:

Cooking Game

Burger Queen



x 4 within 50 ticks

Chef



Sous-Chef



Server



Participant

Pre-registered at

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Study 1:

Cooking Game

Burger Queen

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

Chef



Sous-Chef



Server



Participant

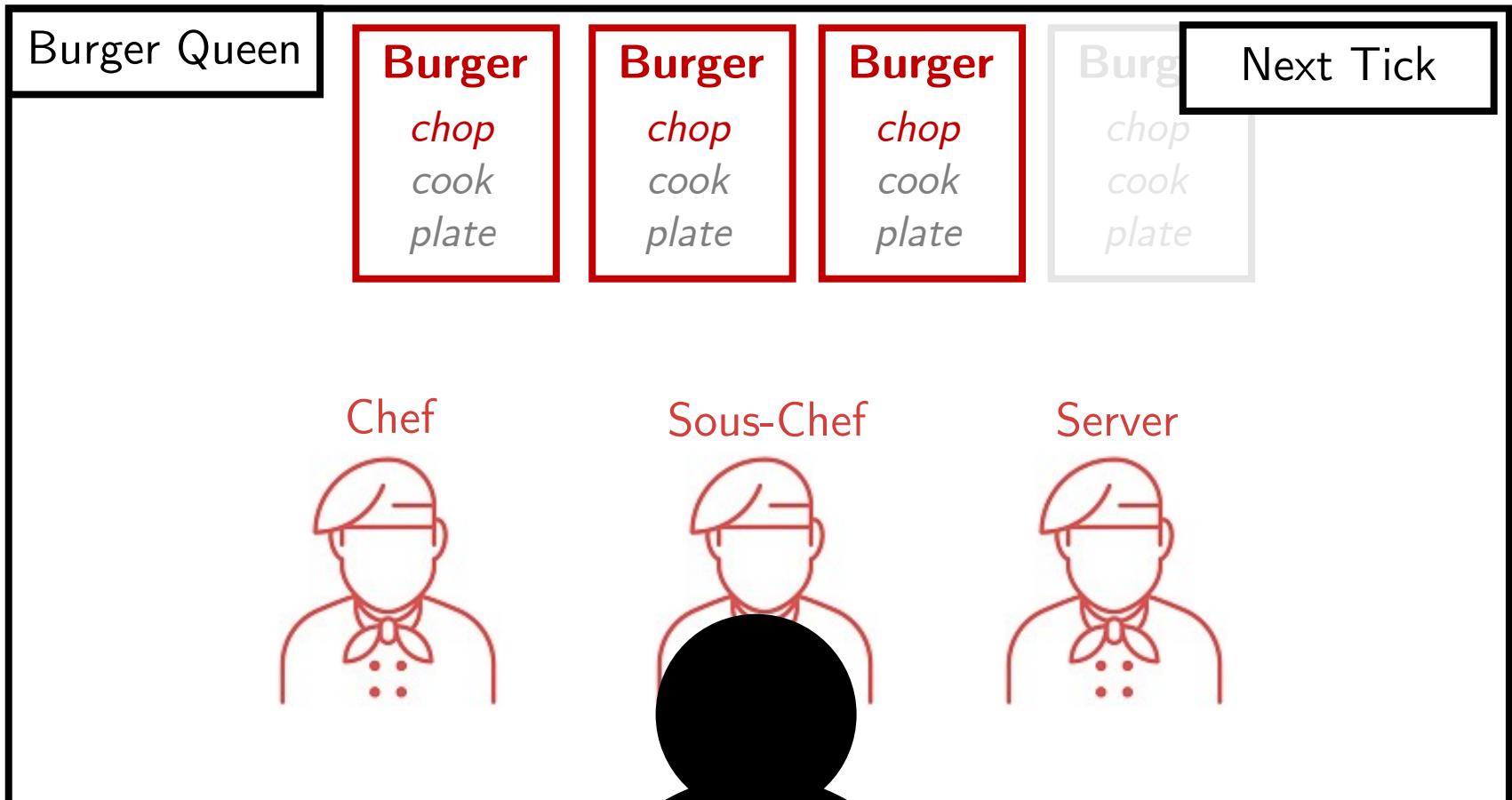
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Study 1:

Cooking Game

Reward: 0
Tick #1/50



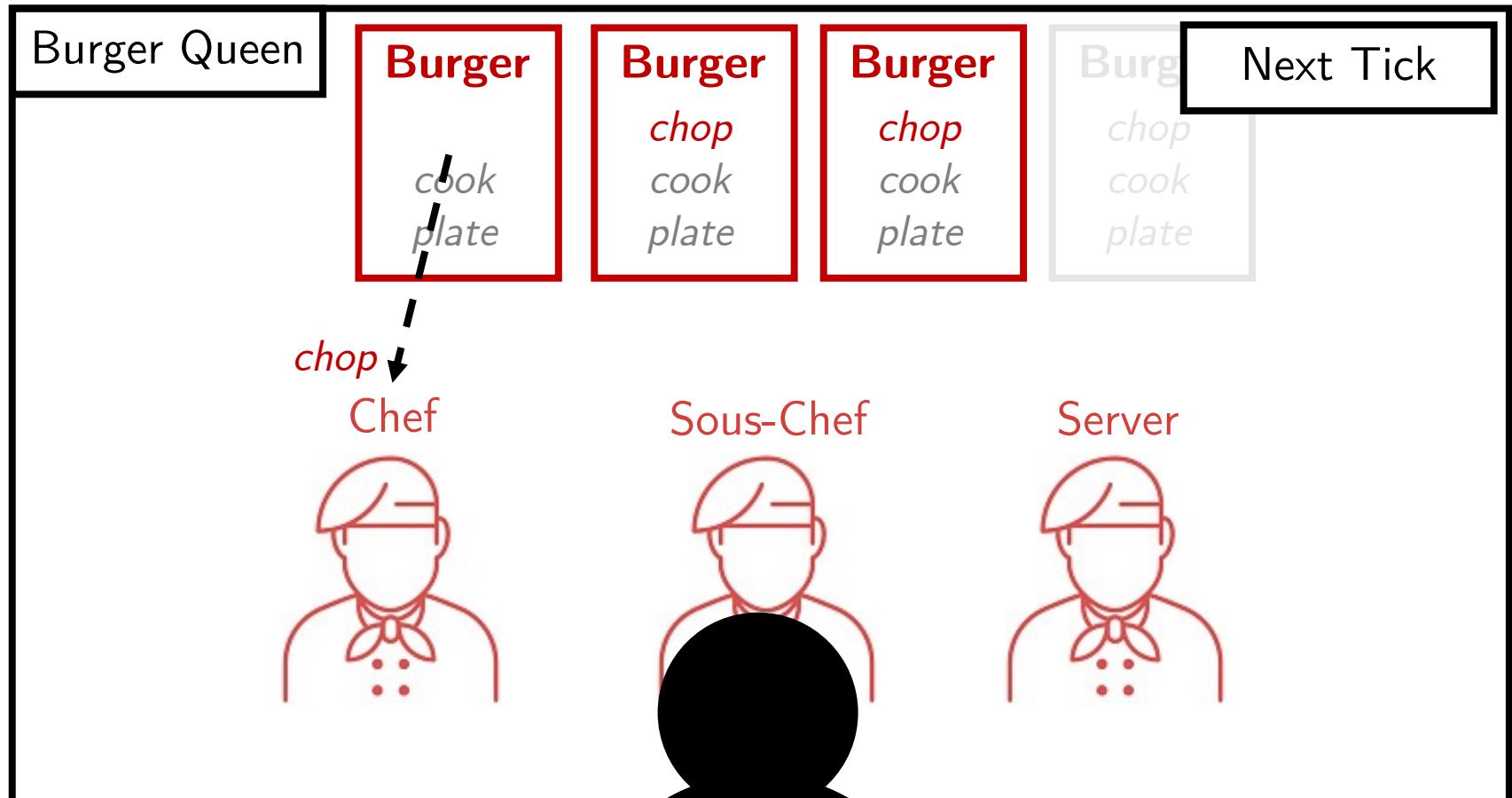
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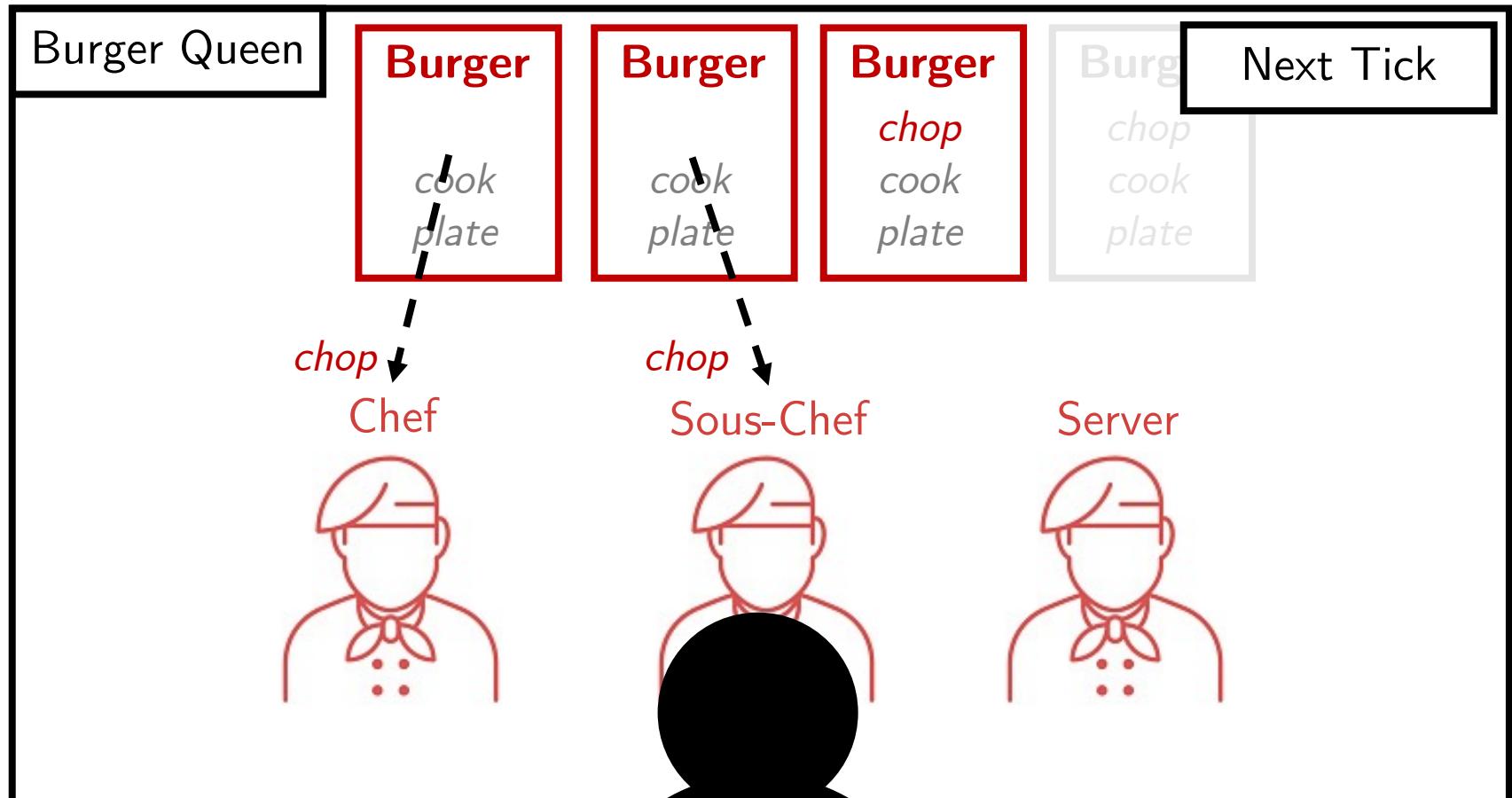
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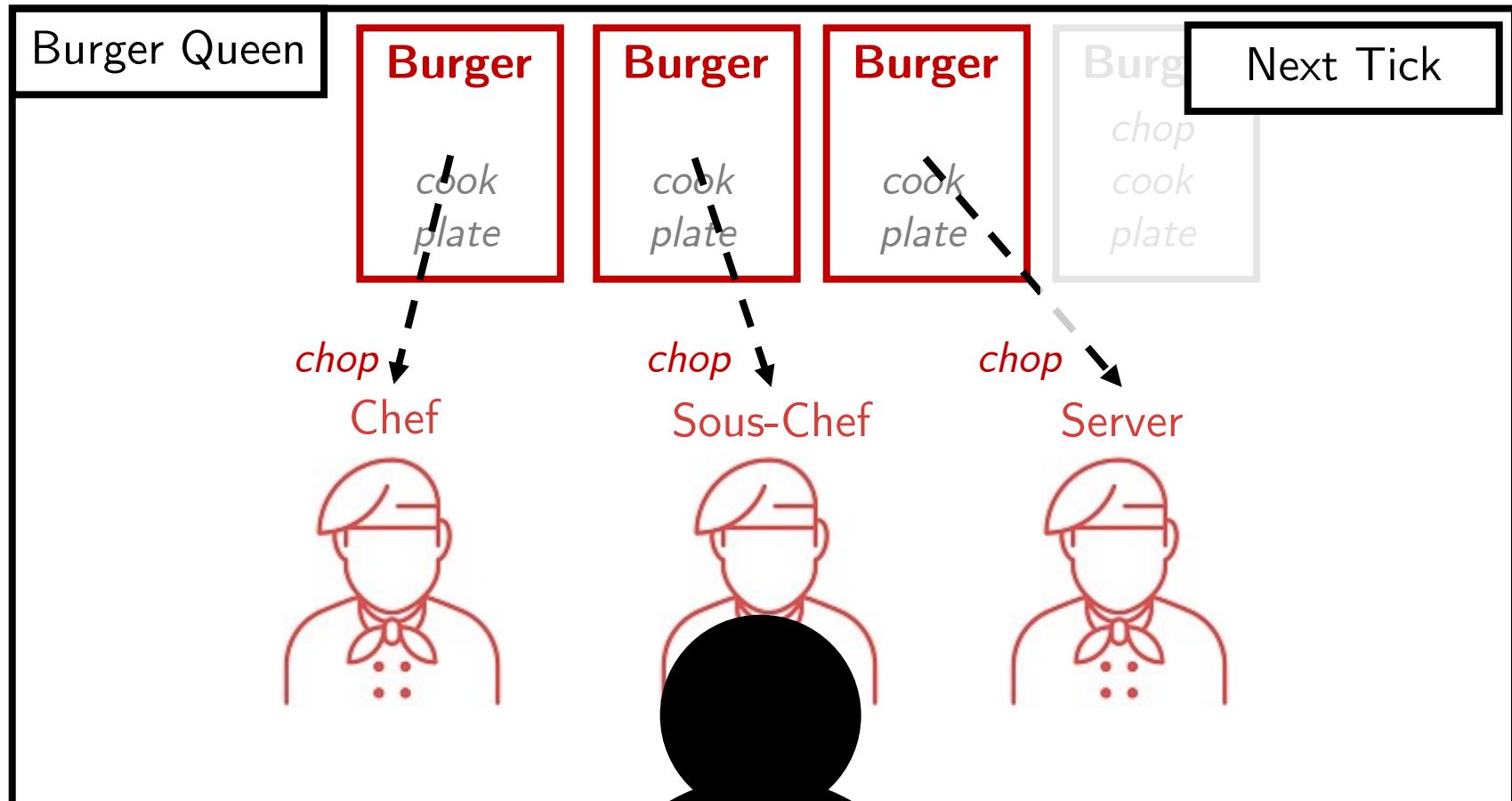
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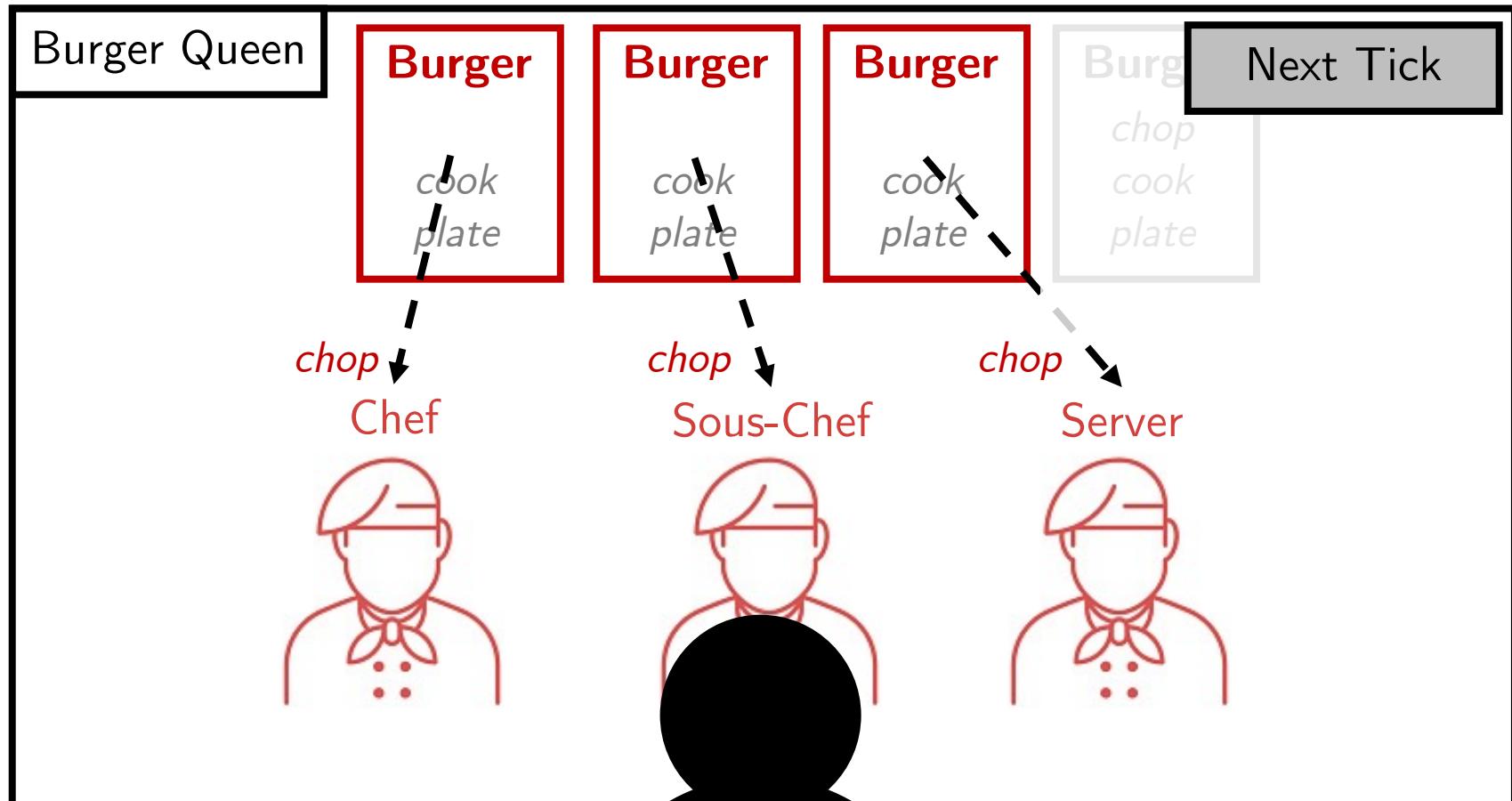
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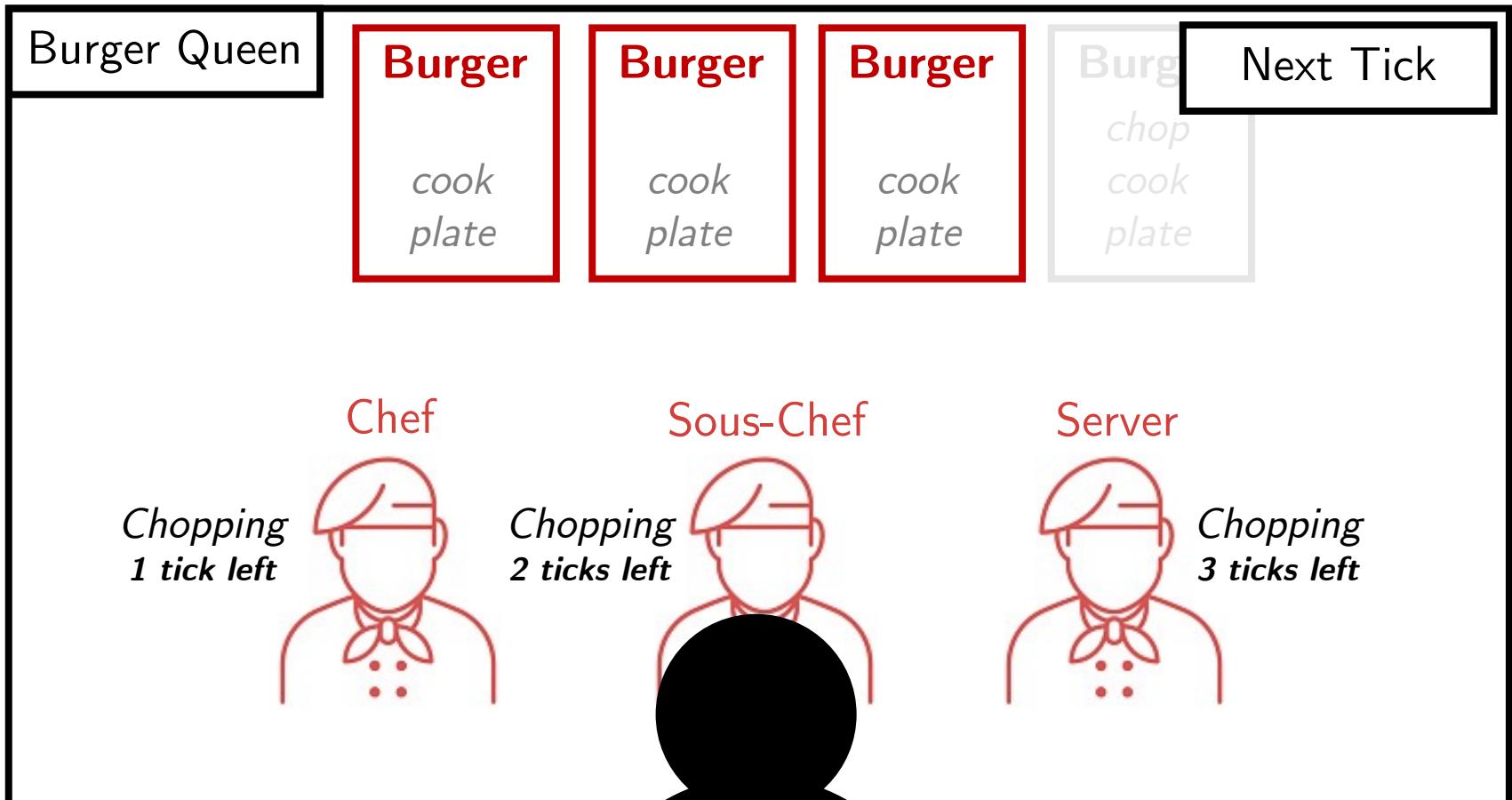
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Participant

Study 1:

Cooking Game

Reward: 0
Tick #2/50



Study 1:

Design

Disruption Scenario



x 4 within 50 ticks

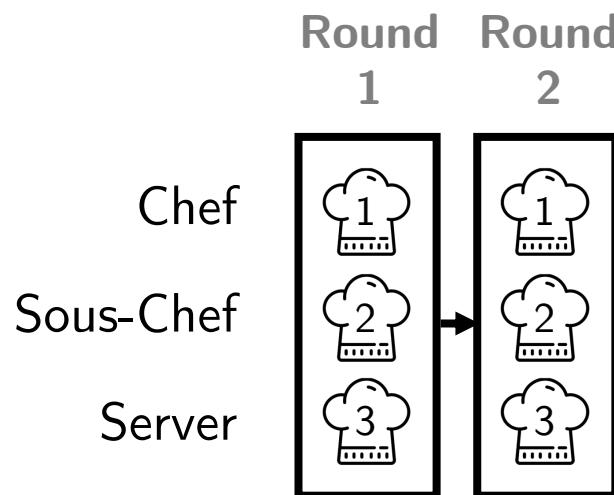
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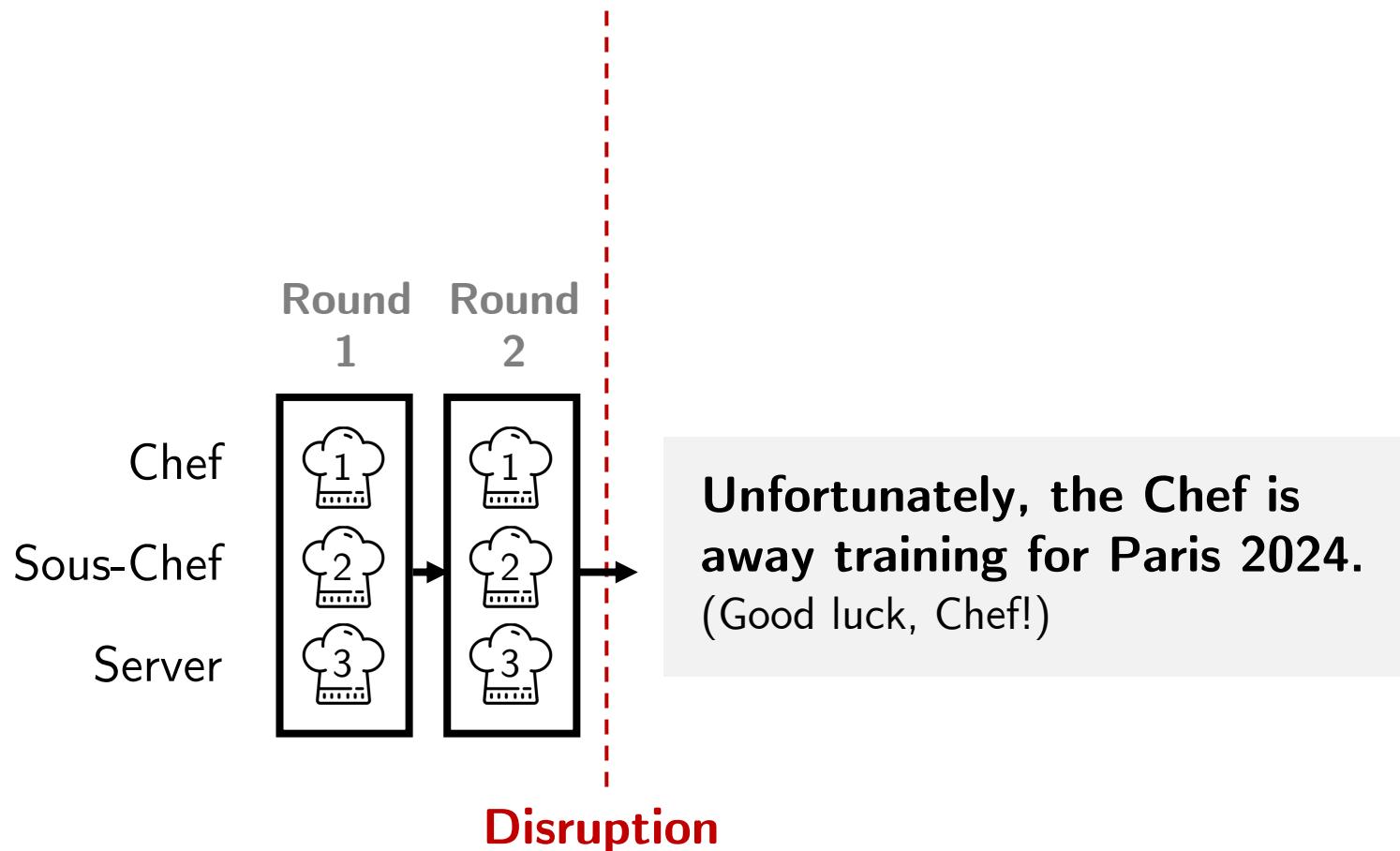
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Disruption Scenario



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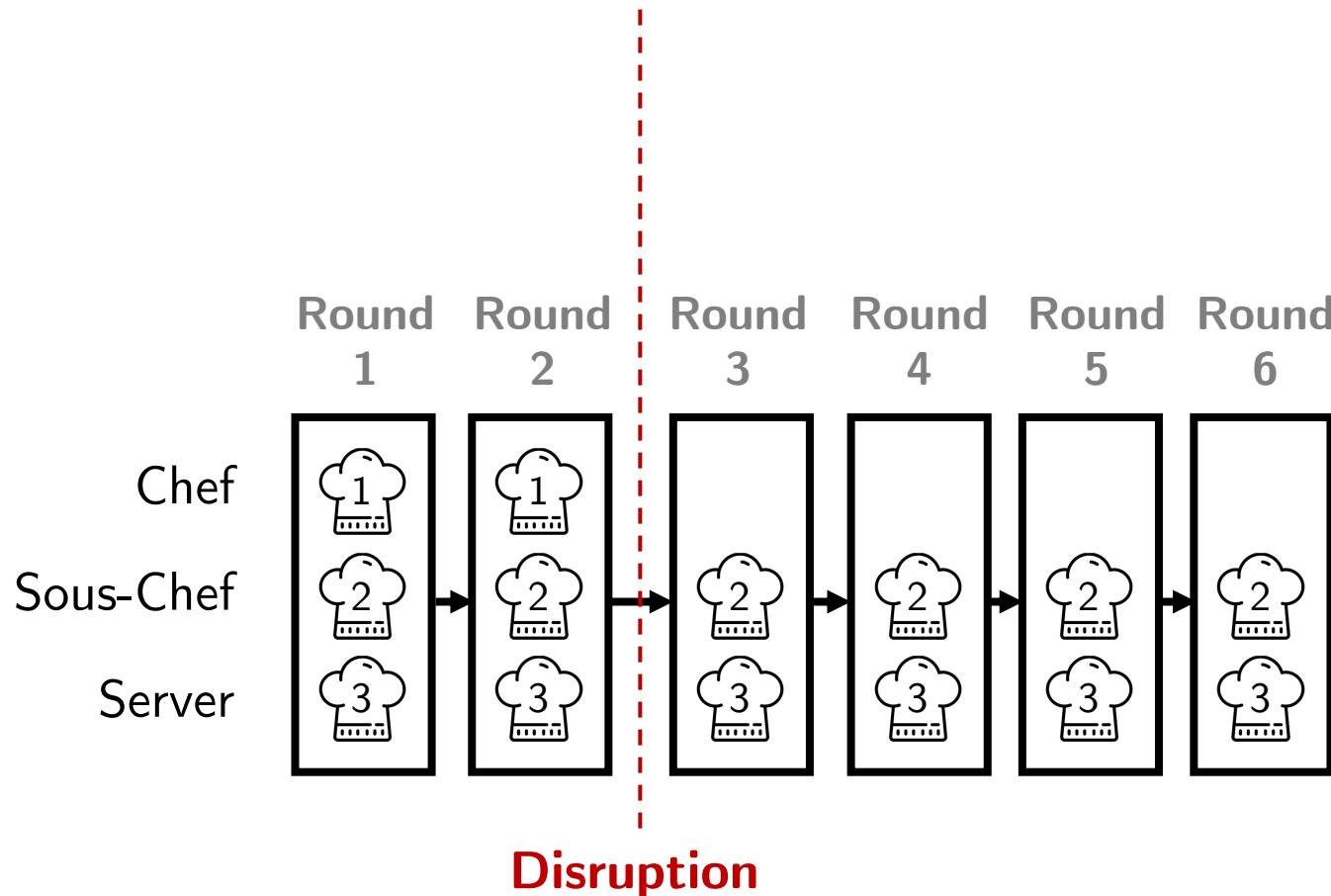
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Design

Disruption Scenario



x 4 within 50 ticks



Problem Formulation

MDP Formulation:

Optimal policy and human make sequences of decisions



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

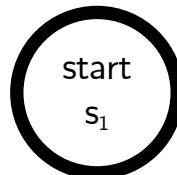
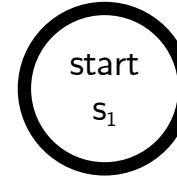
Problem Formulation

MDP Formulation:

Optimal policy and human make sequences of decisions



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 π^*  π 

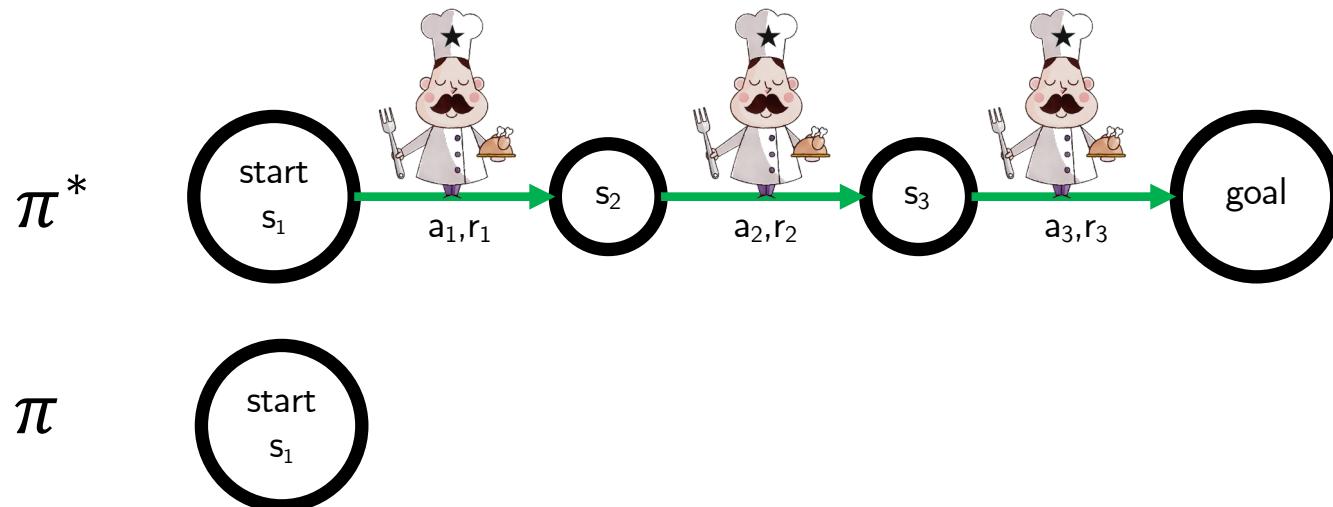
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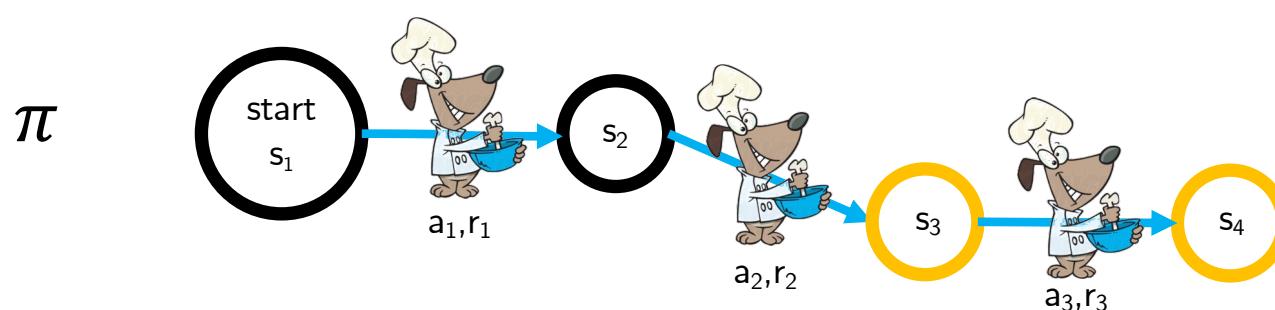
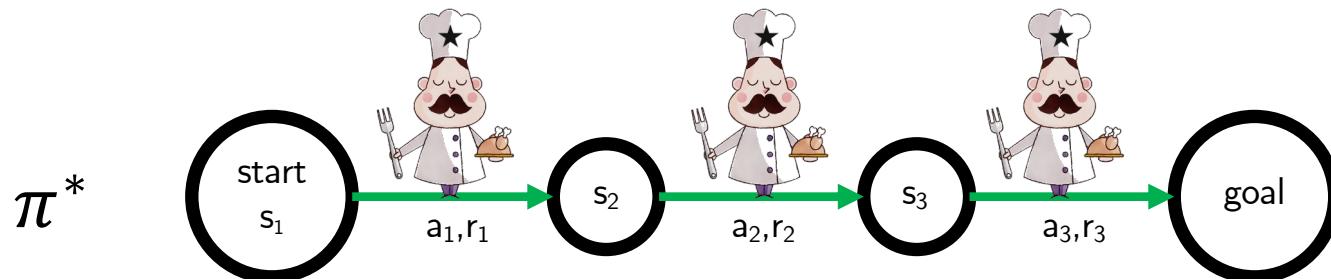
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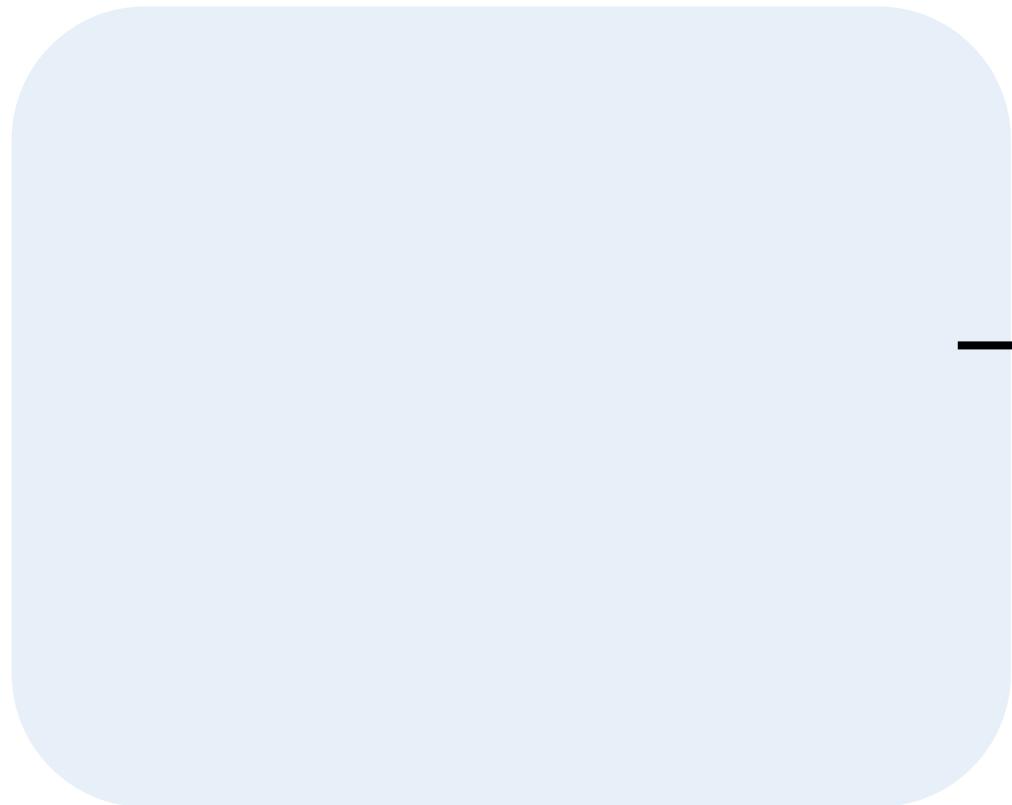
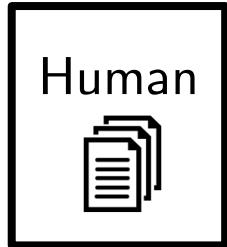
Optimal policy and human make sequences of decisions



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



Our Approach



Tips

Our Approach

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



Input:

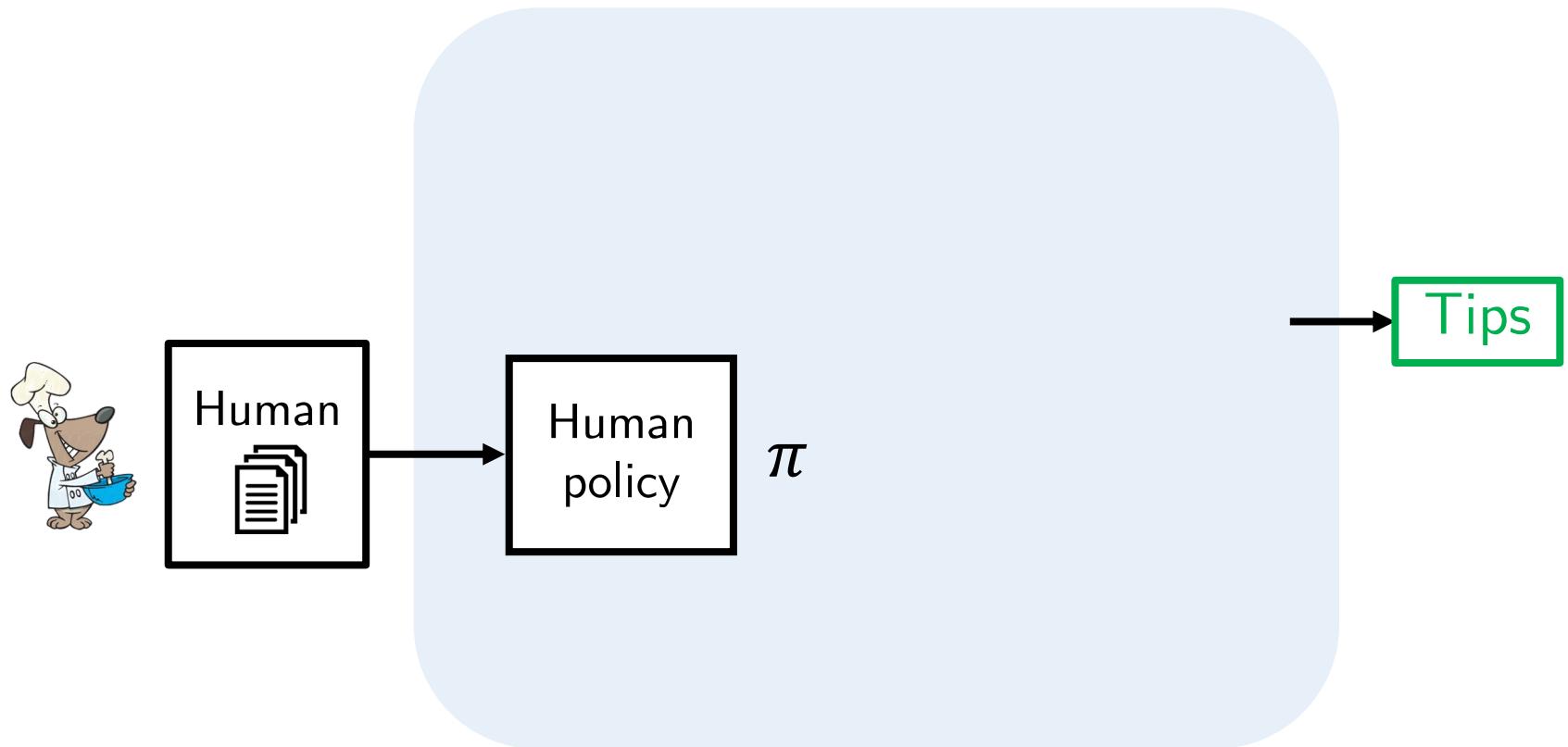
*Trace data \hat{d}_h
from human*

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

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

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



π

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

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

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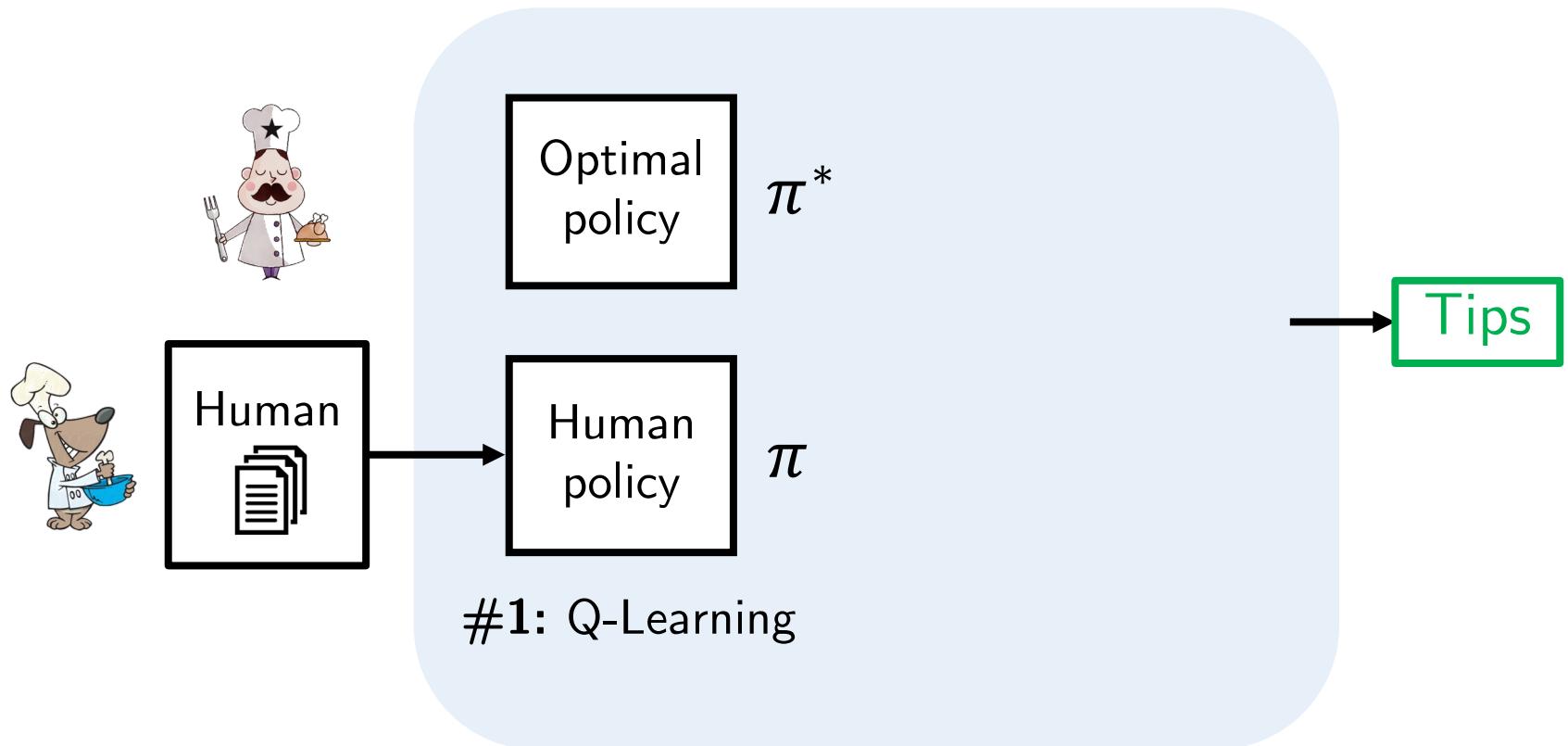
- Watkins & Dayan 1992

- Learn using supervised learning on trace data obtained using π

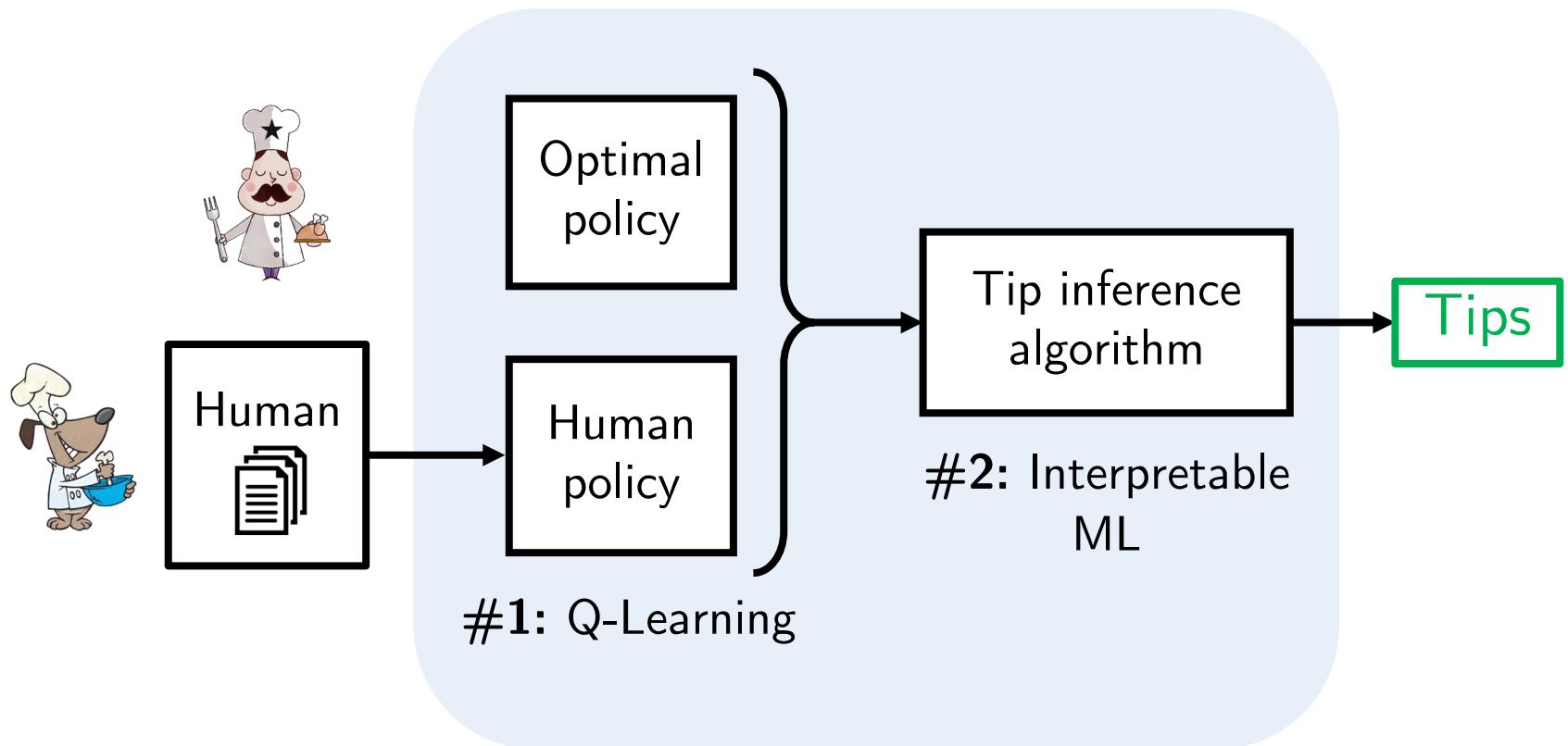
$$\hat{Q}_\theta^\pi(s, a) \approx Q^\pi(s, a)$$

Our Approach

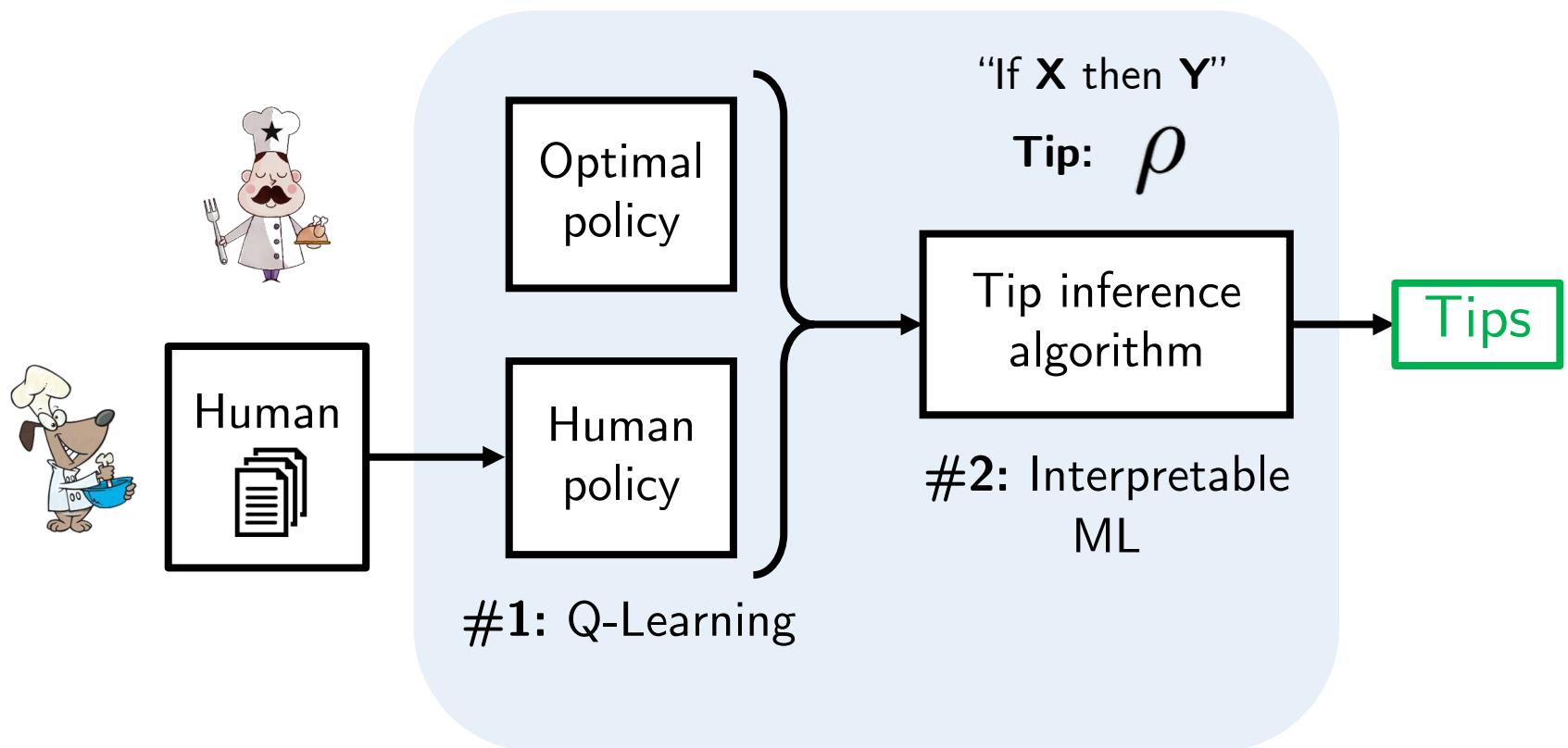
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Our Approach



Our Approach



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

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

Human policy + tip **Only human policy**

- $\pi_h \oplus \rho$ denotes overriding the human policy with tip ρ .

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Human policy + tip **Only human policy**

- $\pi_h \oplus \rho$ 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

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

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

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

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

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Assign chef to cook the first 2 burgers

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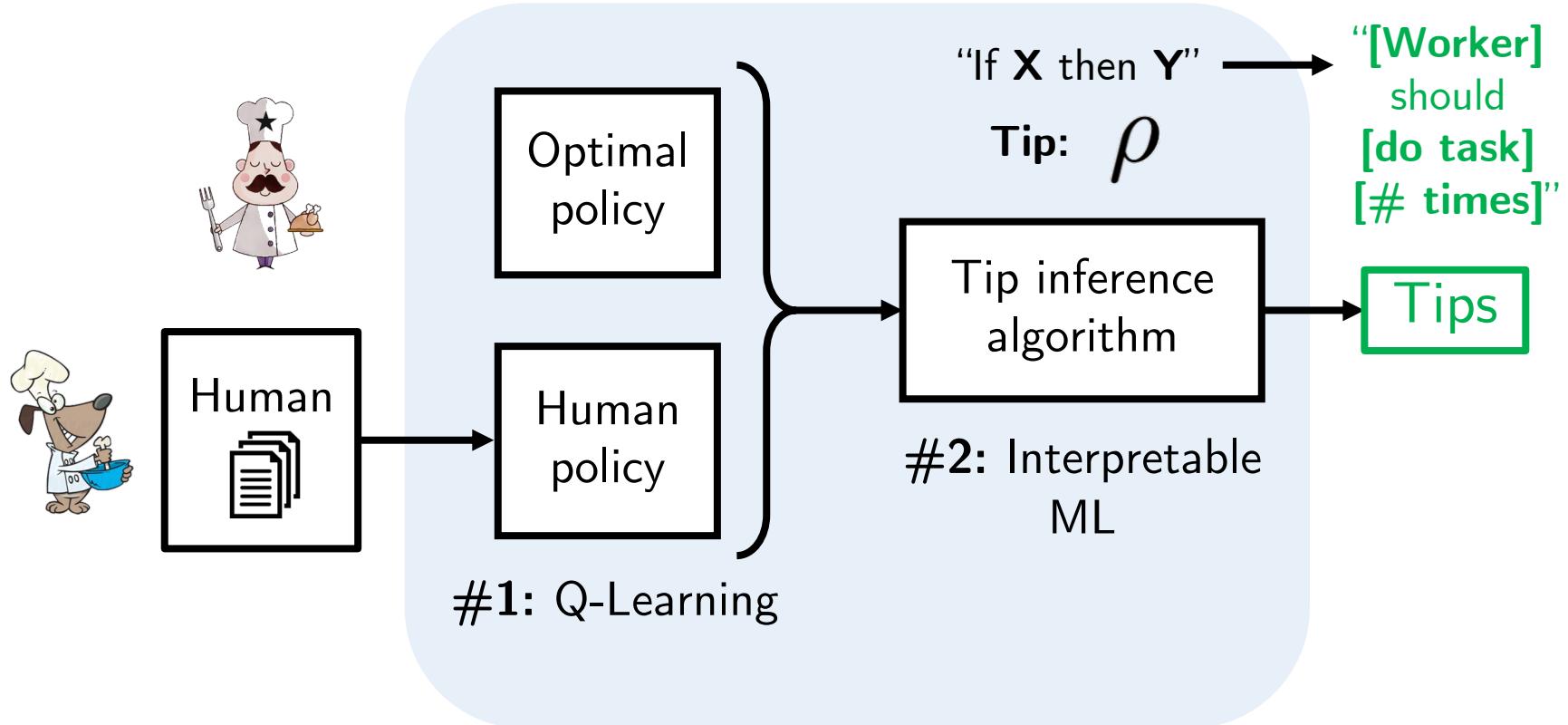


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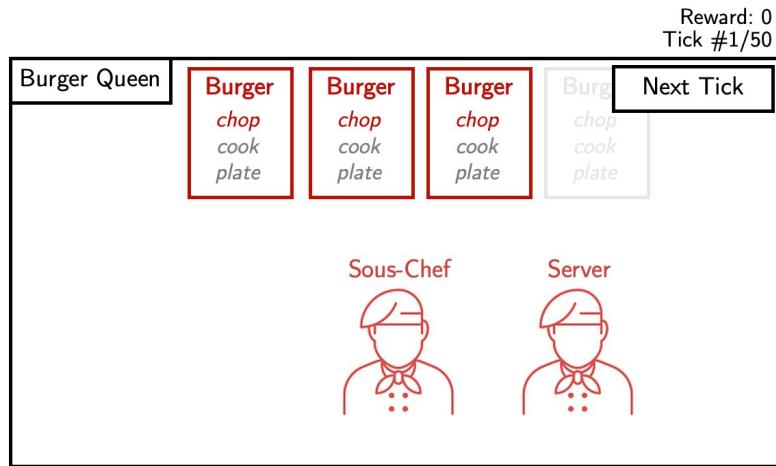


Chef should cook twice

Our Approach

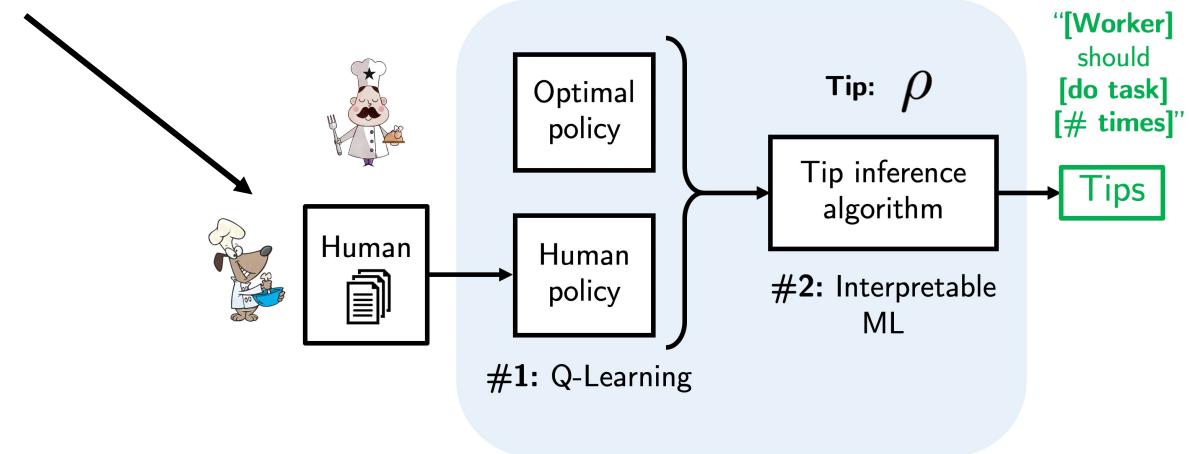
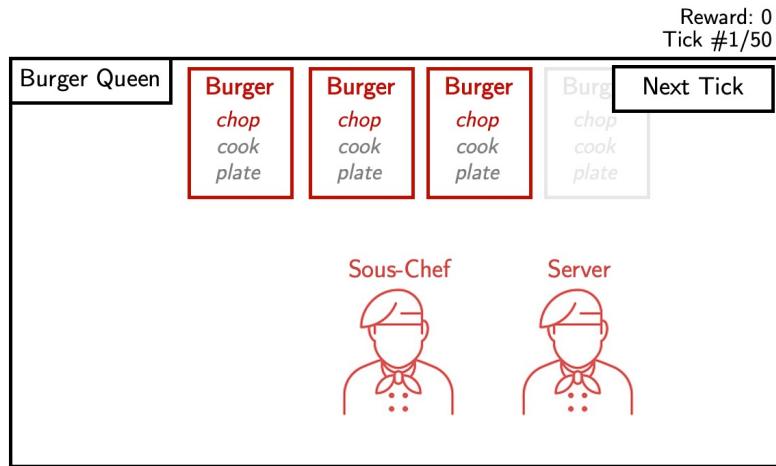


Phase I Collect Trace Data



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

Human

Server
should cook twice

*Most frequent tip
chosen by participants*

Phase I Inferred Tips

Algorithm

Server
should cook twice

Human

Server
should cook once

*Most frequent tip
chosen by participants*

Phase I Inferred Tips

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

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
<i>Most frequent tip chosen by participants</i>		
<i>Most frequent s-a deviation b/w optimal and trainee policies</i>		

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

Control

- No tip -

Algorithm

Server
should cook twice

Human

Server
should cook once

Baseline

Sous-Chef
should plate twice

Phase II

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

Control

- No tip -

Algorithm

Server
should cook twice

Tip:

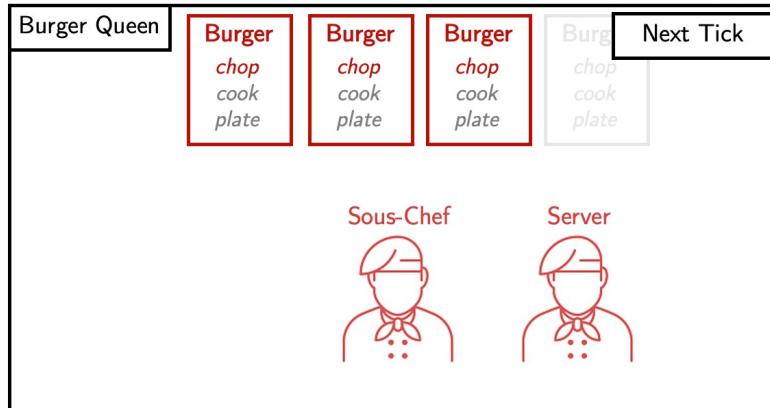
Human

Server
should cook once

Baseline

Sous-Chef
should plate twice

Reward: 0
Tick #1/50



Phase II

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

Algorithm vs Human

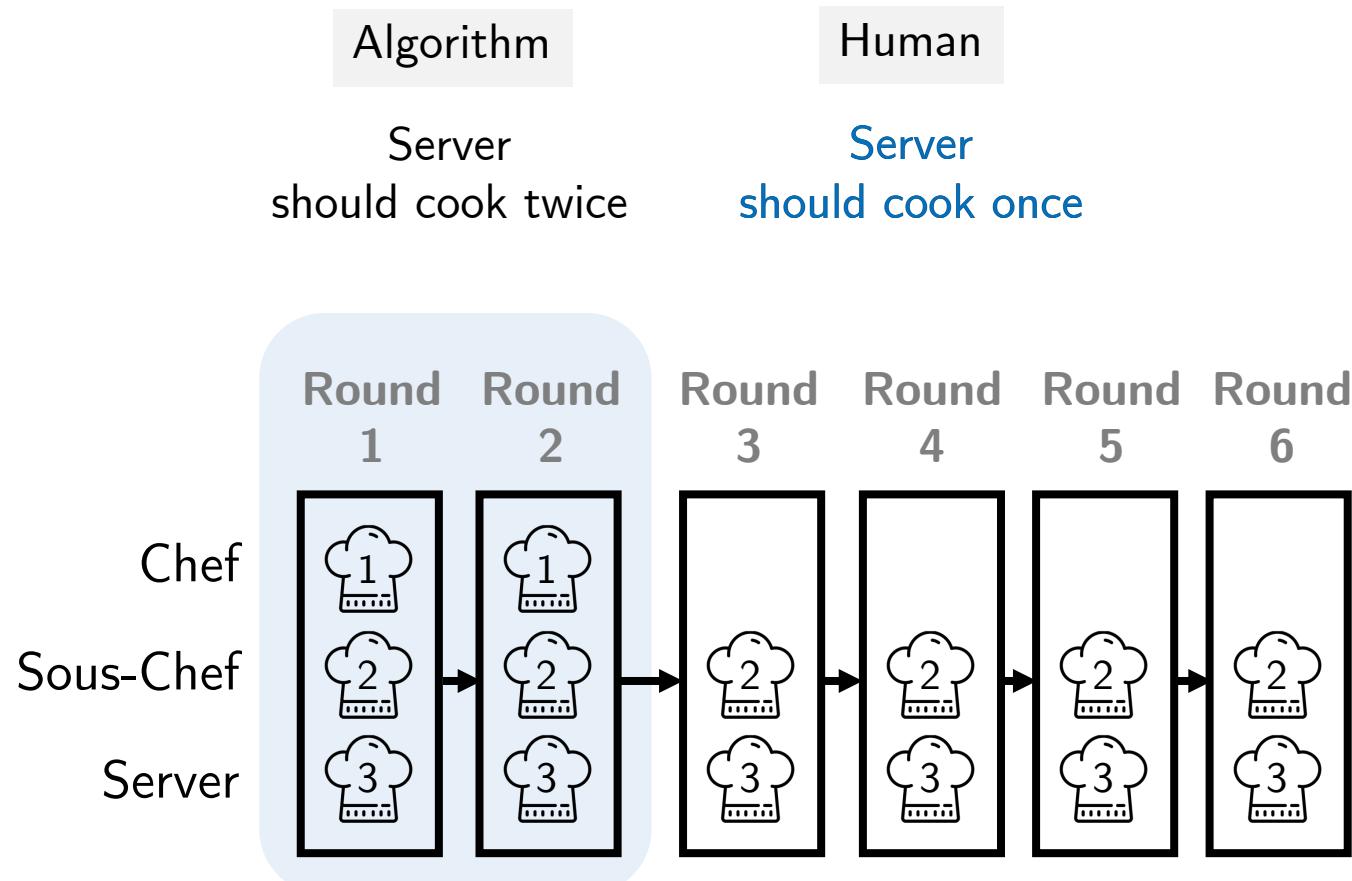
Algorithm

Server
should cook twice

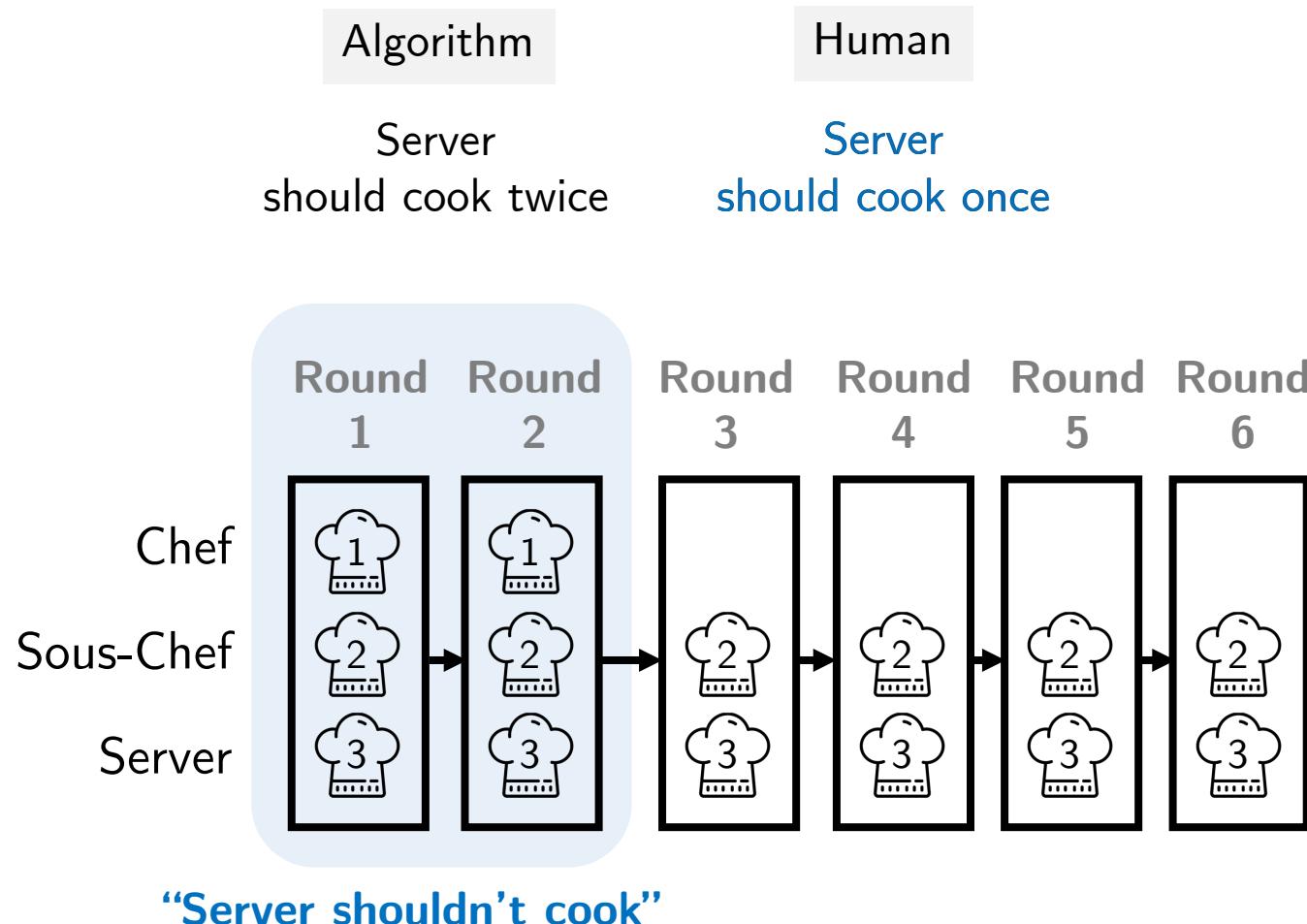
Human

Server
should cook once

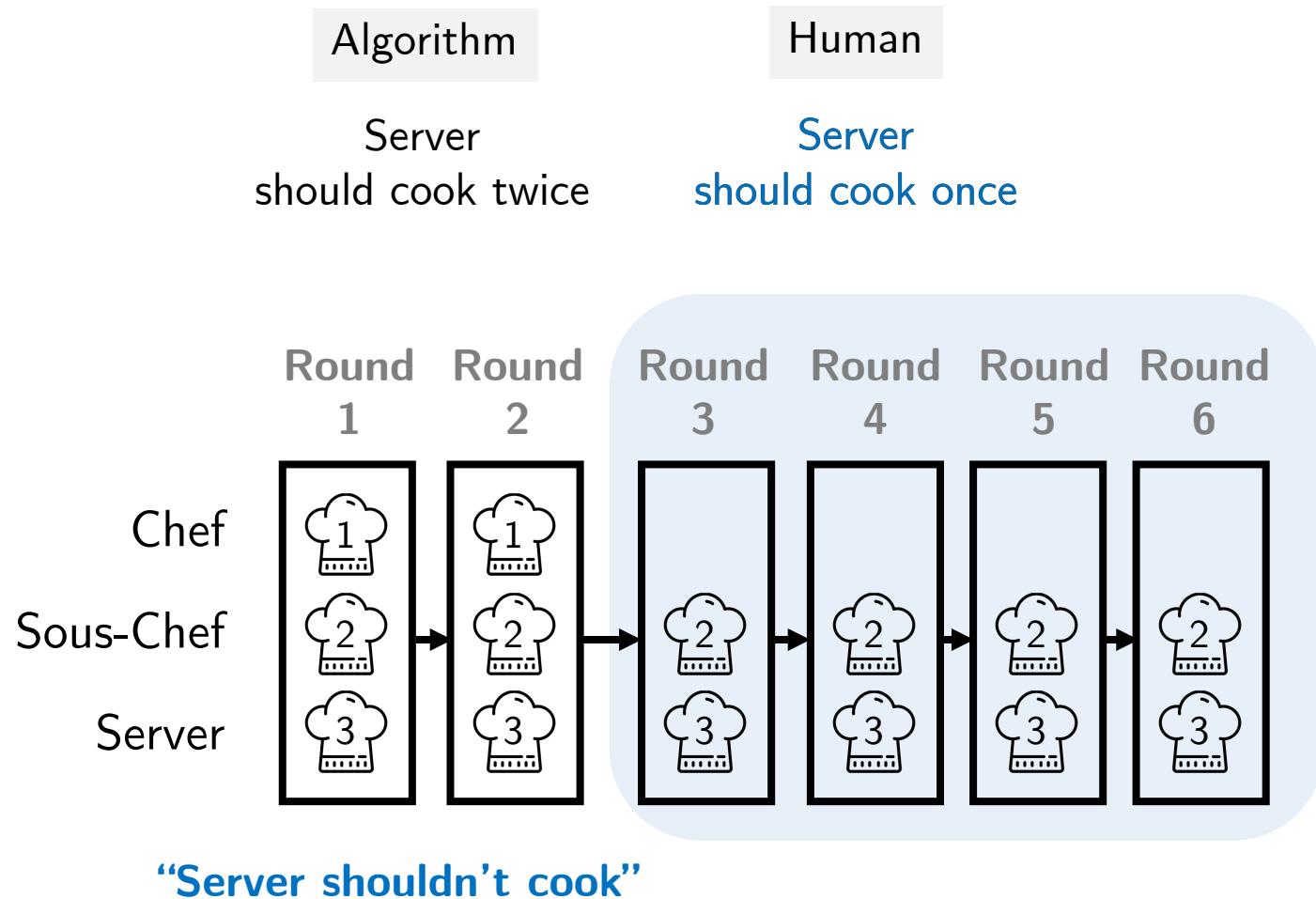
Algorithm vs Human



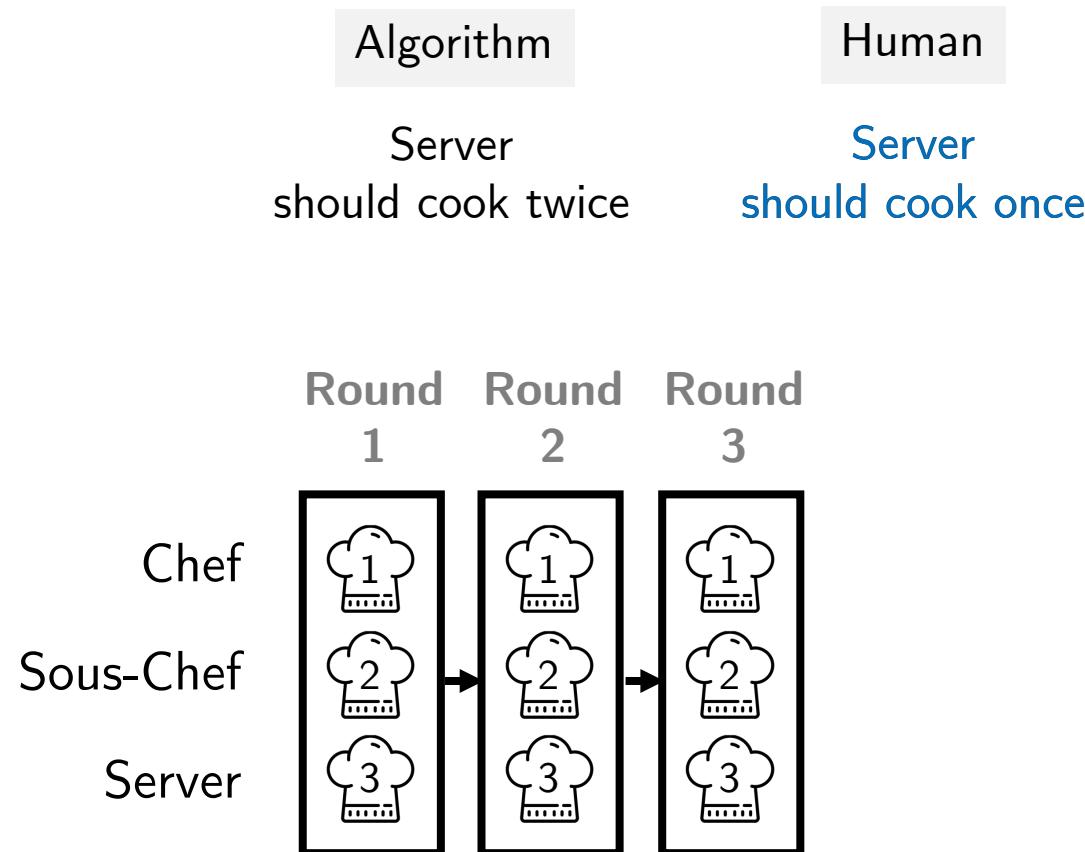
Algorithm vs Human



Algorithm vs Human

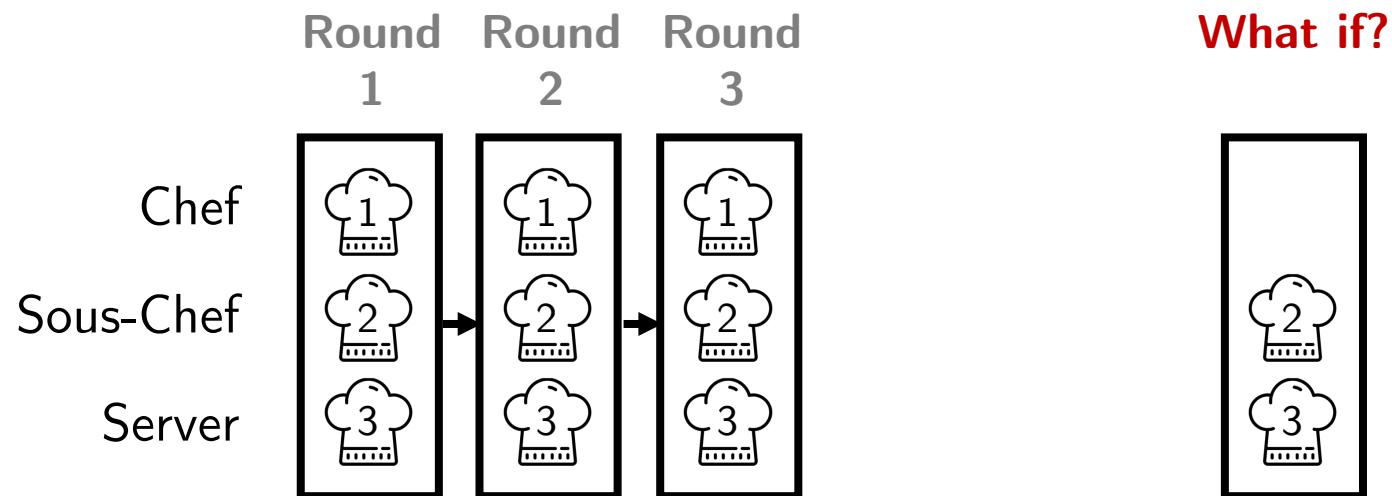


Algorithm vs Human



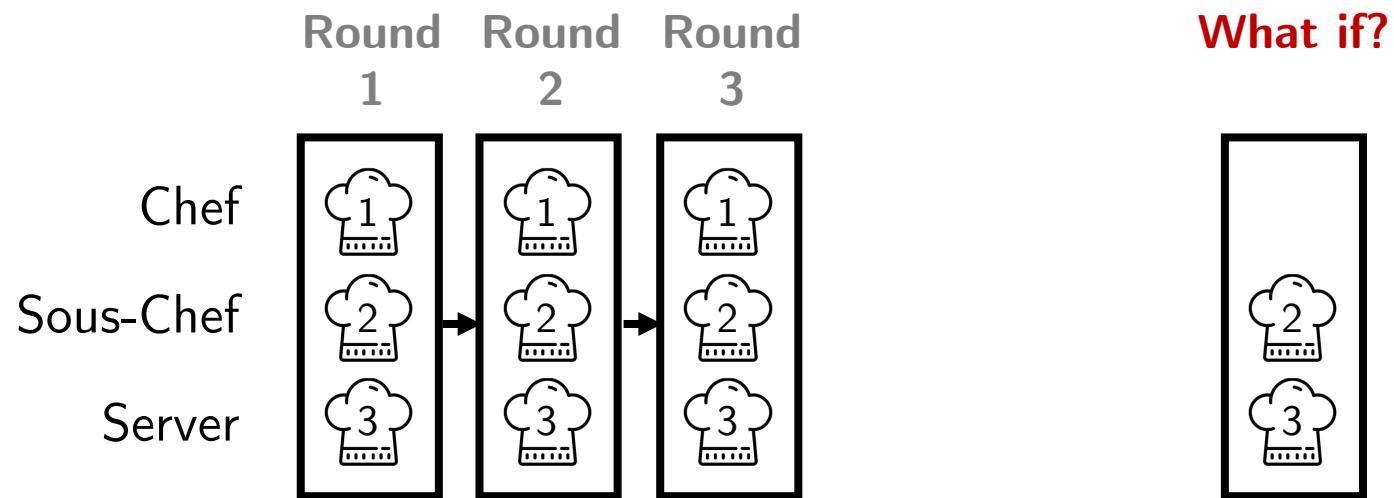
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once

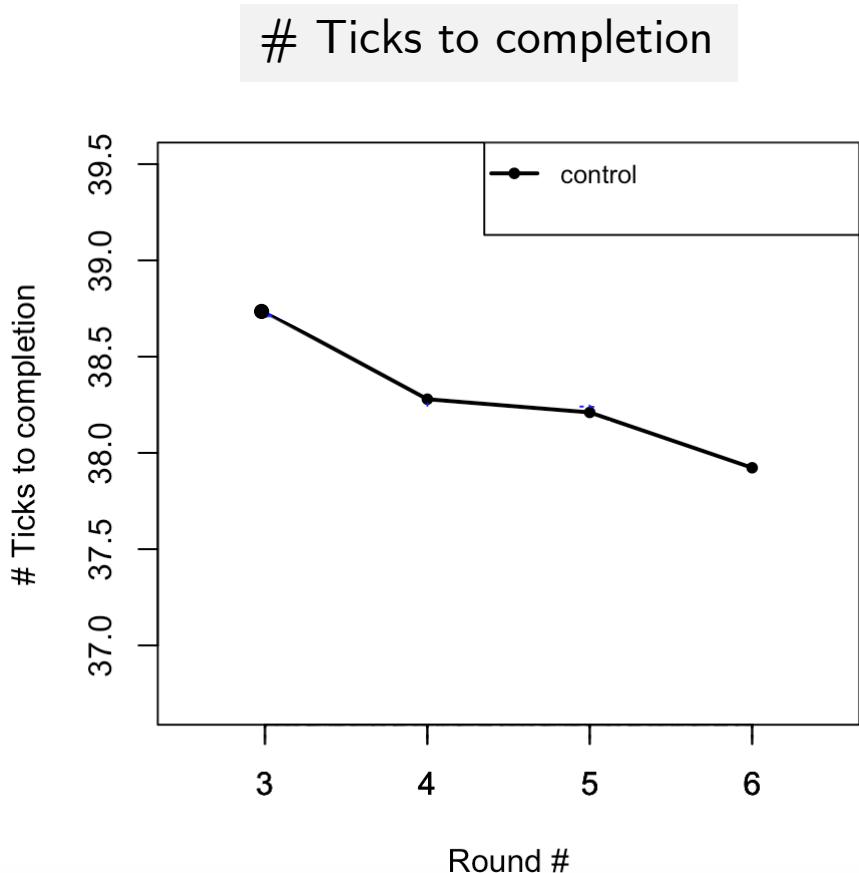


Algorithm vs Human

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

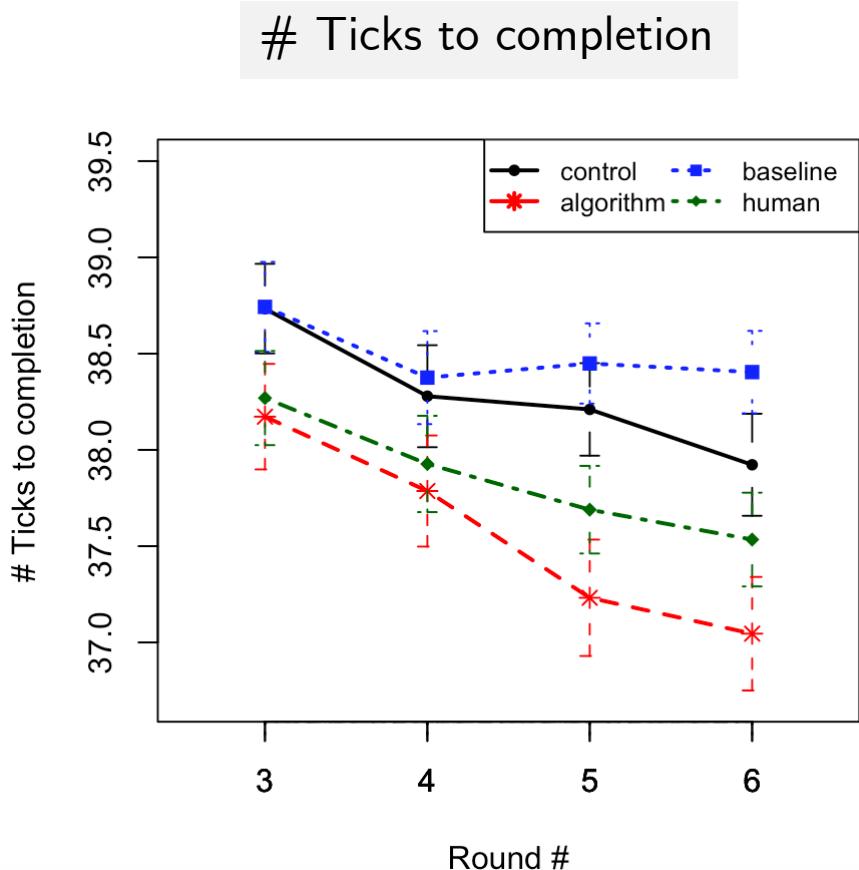


Study 1: Results People Improve Over Time



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

Study 1: Results Our Tip Improves Performance

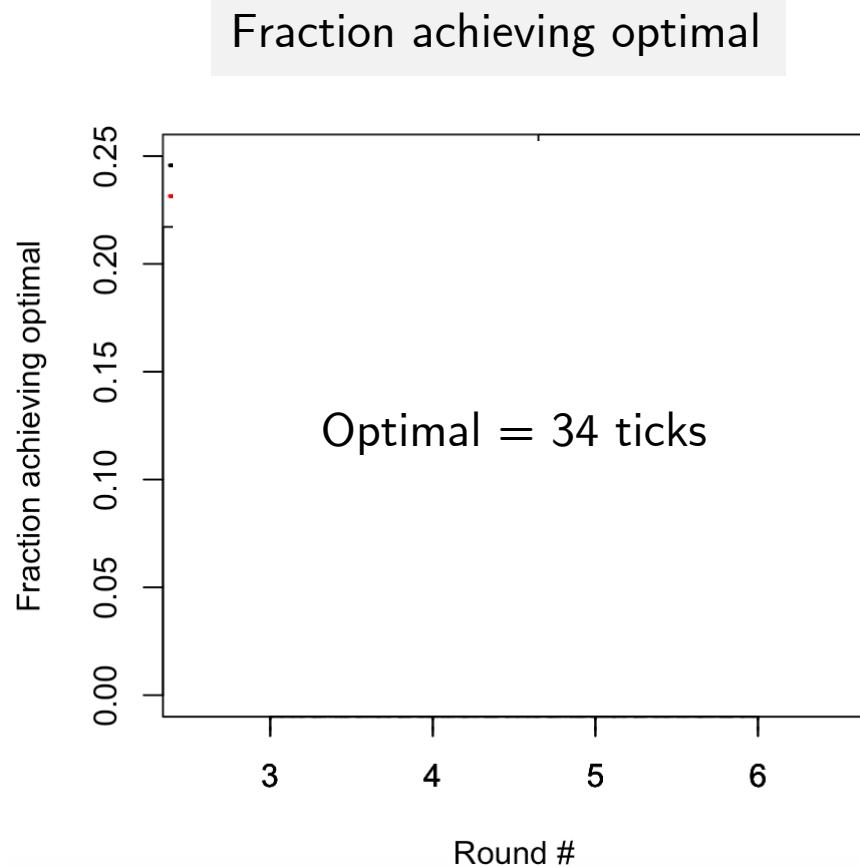
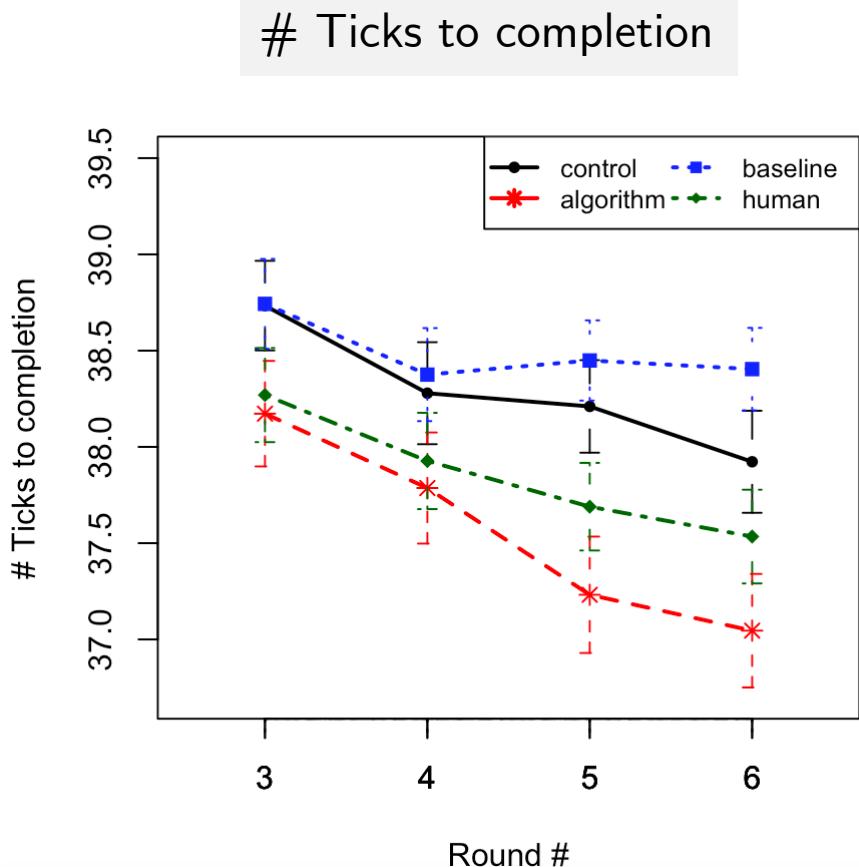


One-sided T-Tests

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



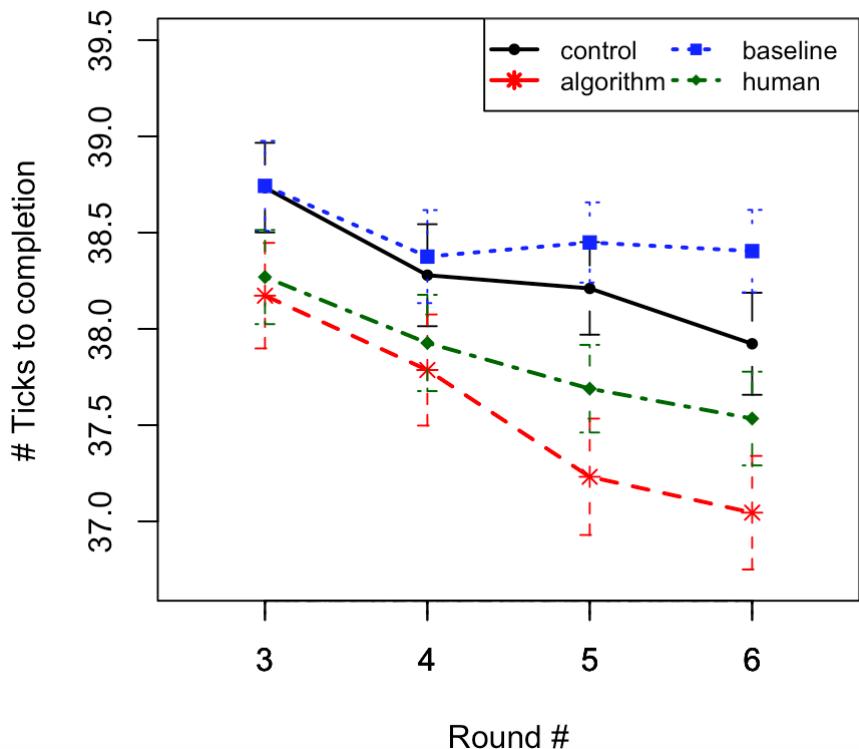
Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Study 1:

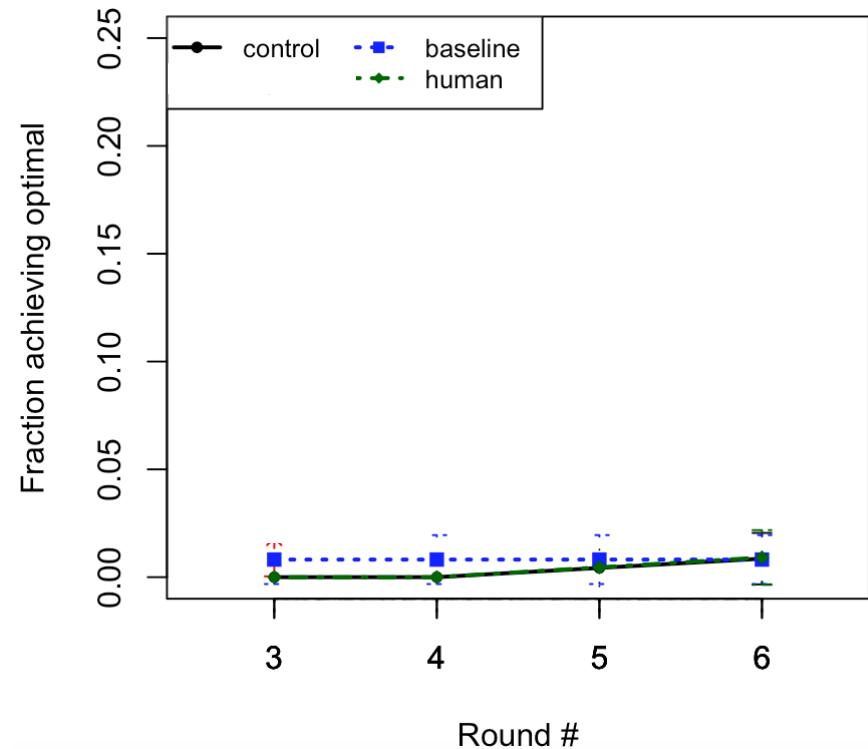
Results

Difficult to Reach Optimal

Ticks to completion



Fraction achieving optimal



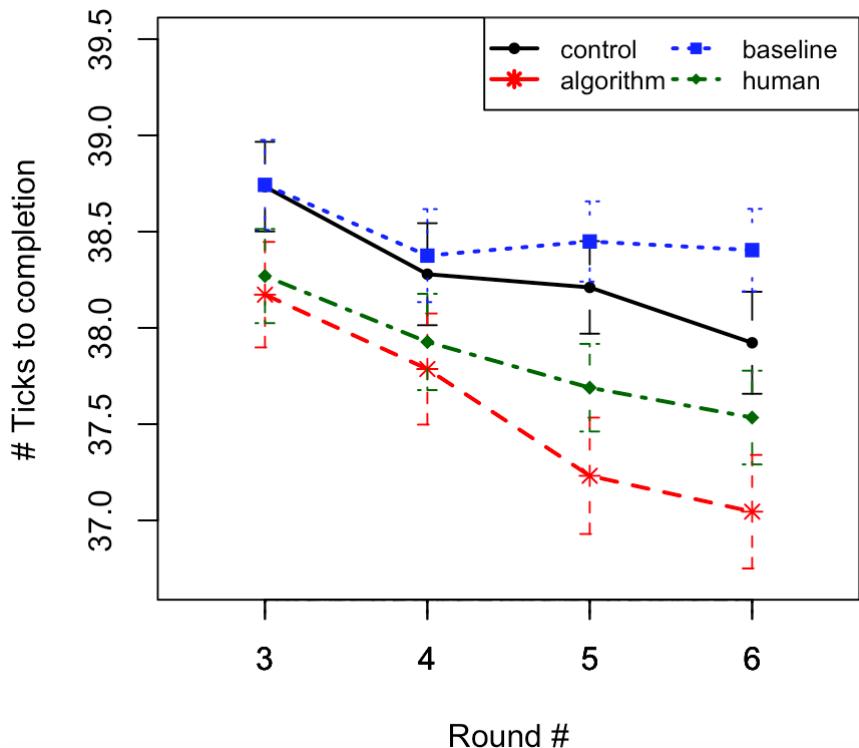
Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Study 1:

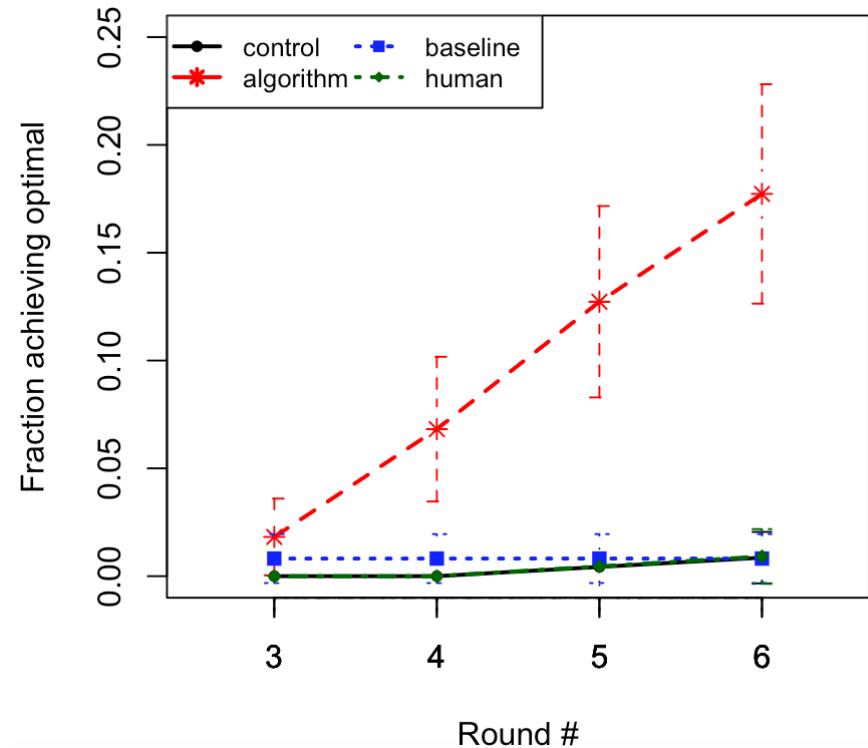
Results

Our Tip Helps Reach Optimal

Ticks to completion

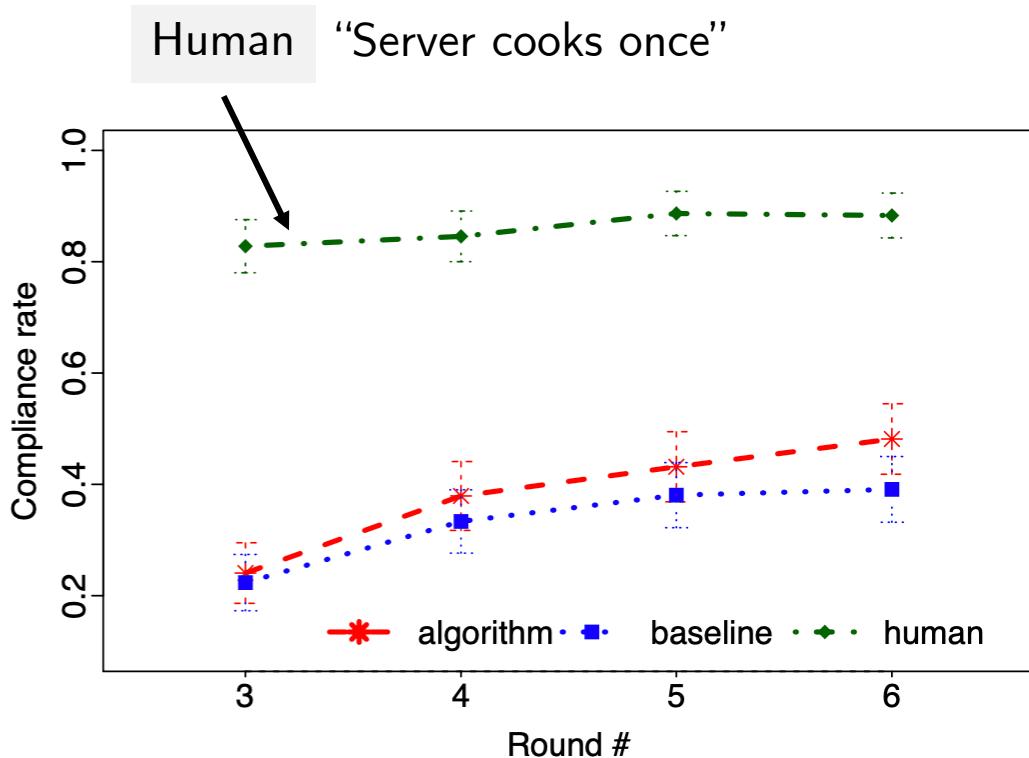


Fraction achieving optimal



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

Study 1: Results Complying with Intuitive Tip

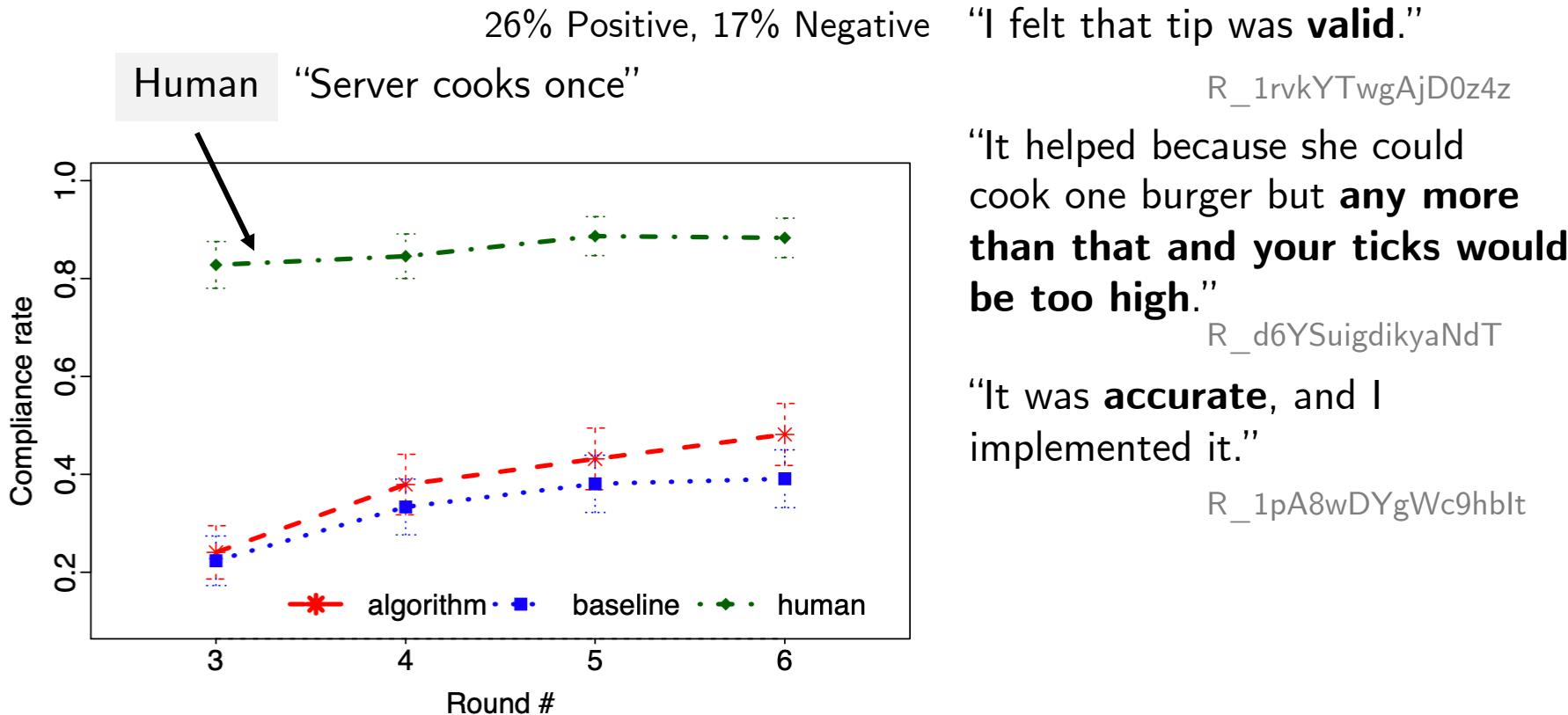


Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Study 1:

Results

Complying with Intuitive Tip

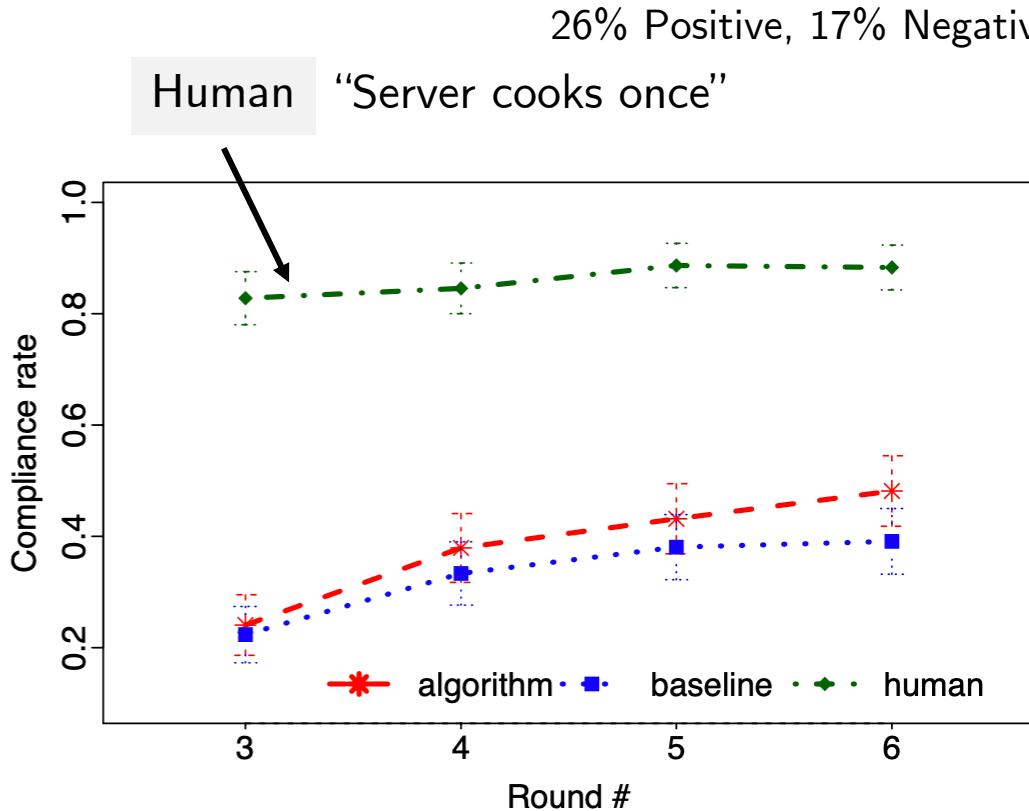


Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Study 1:

Results

Complying with Intuitive Tip



“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.”

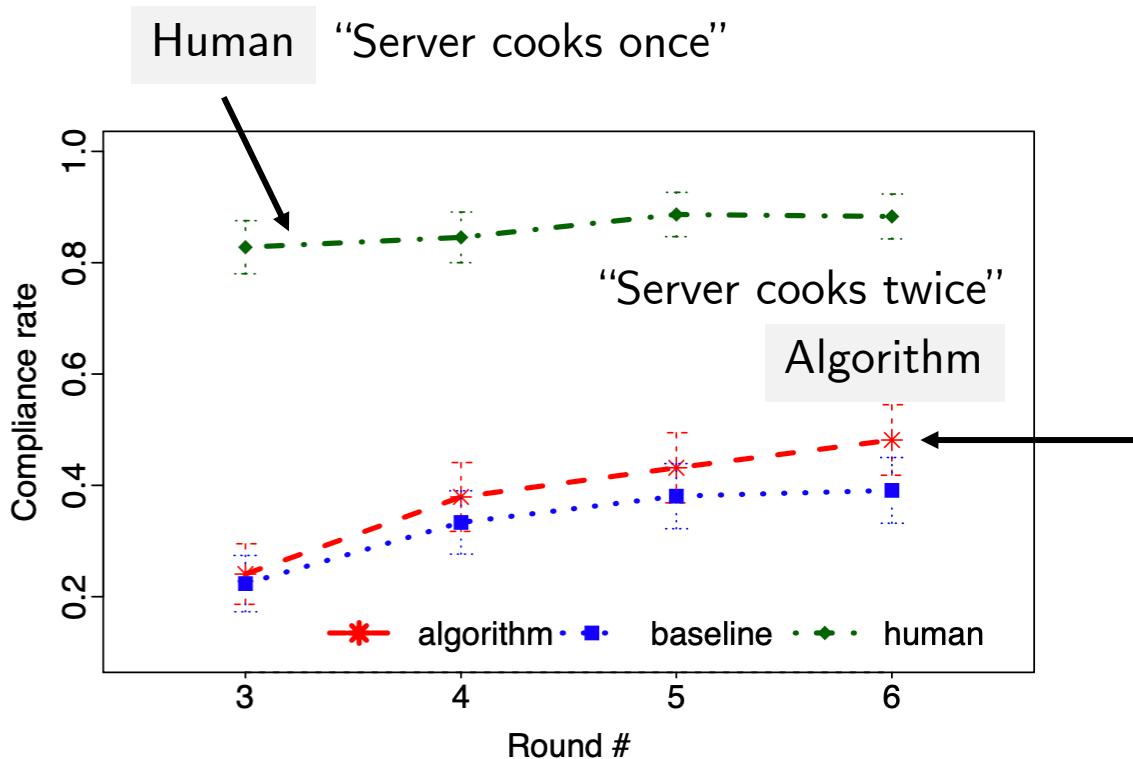
R_1pA8wDYgWc9hbIt

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

R_beijQ8guDyExa5r

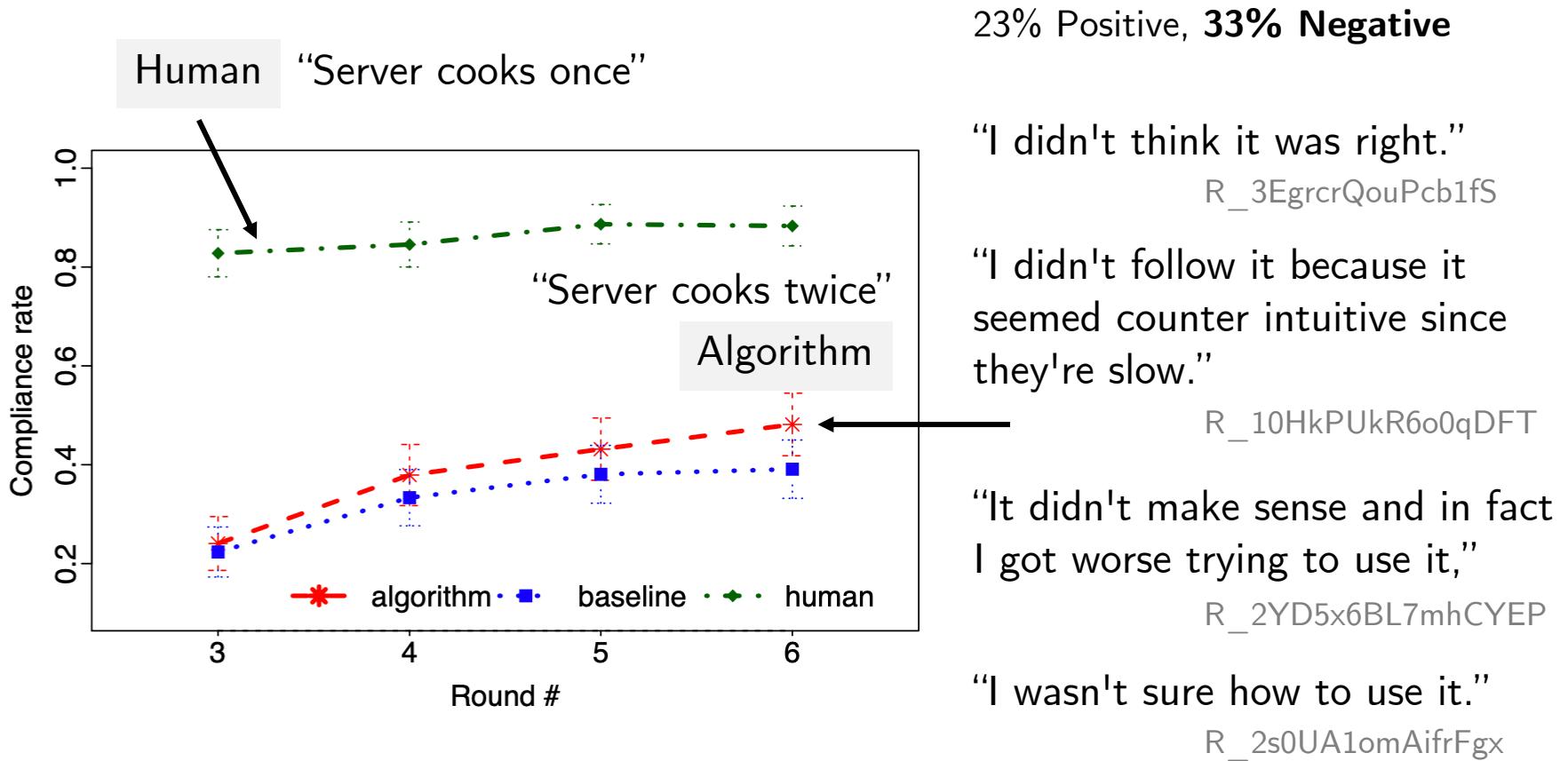
“I used the tip but **I don’t think it was helpful**. The server took long to cook.”

Study 1: Results Against Counterintuitive Tips



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

Study 1: Results Against Counterintuitive Tips



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

Improving Compliance?

Improving Compliance

Social information

Here's how you compare to neighbors



Aug 21, 2015 - Sep 20, 2015

This is based on 87 similar homes within approx. 4 miles. Efficient neighbors are the 20% who use the least amount of electricity.
See back for details.



You're using more than
your neighbors.



8% more electricity
than average neighbors

Allcott 2011, *Journal of Public Economics*

Improving Compliance

Social information

“The best players always used this strategy:
Server cooks twice.”

Improving Compliance

Social information

“The best players always used this strategy:
Server cooks twice.”

Incentive to try

Improving Compliance

Social information

“The best players always used this strategy:
Server cooks twice.”

Incentive to try

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

Improving Compliance

Social information

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“Curriculum” – pacing learning

Improving Compliance

Social information

“The best players always used this strategy:
Server cooks twice.”

Incentive to try

“You’ll earn the maximum bonus
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“Curriculum” – pacing learning

Algorithm

Server
should cook twice

Human

Server
should cook once

Hypothetical

Server
shouldn’t cook

Improving Compliance

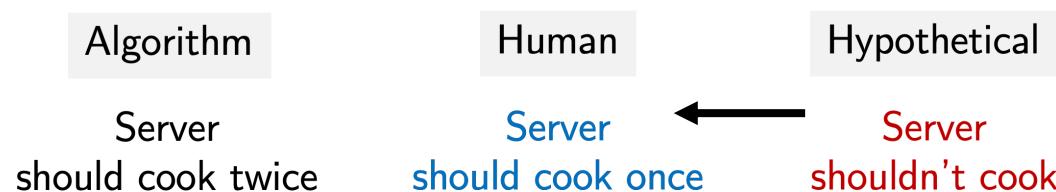
Social information

“The best players always used this strategy:
Server cooks twice.”

Incentive to try

“You’ll earn the maximum bonus
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“Curriculum” – pacing learning



Improving Compliance

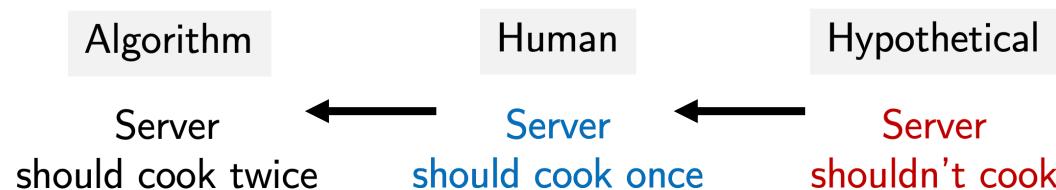
Social information

“The best players always used this strategy:
Server cooks twice.”

Incentive to try

“You’ll earn the maximum bonus
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“Curriculum” – pacing learning



Improving Compliance

Interventions based on incentives, social information, and pace

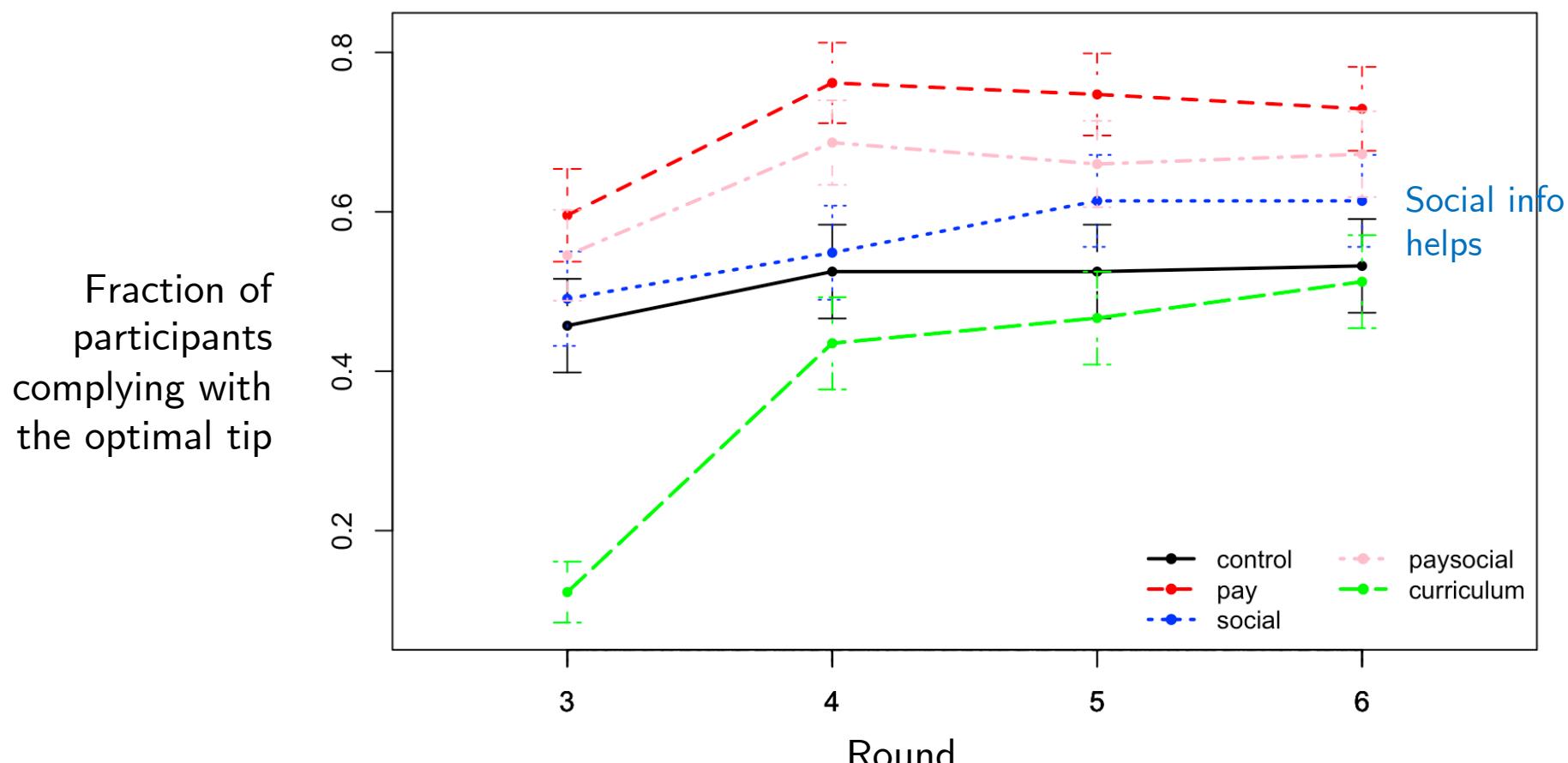
Fraction of
participants
complying with
the optimal tip

Round

Amazon Mechanical Turk, N = 1,416

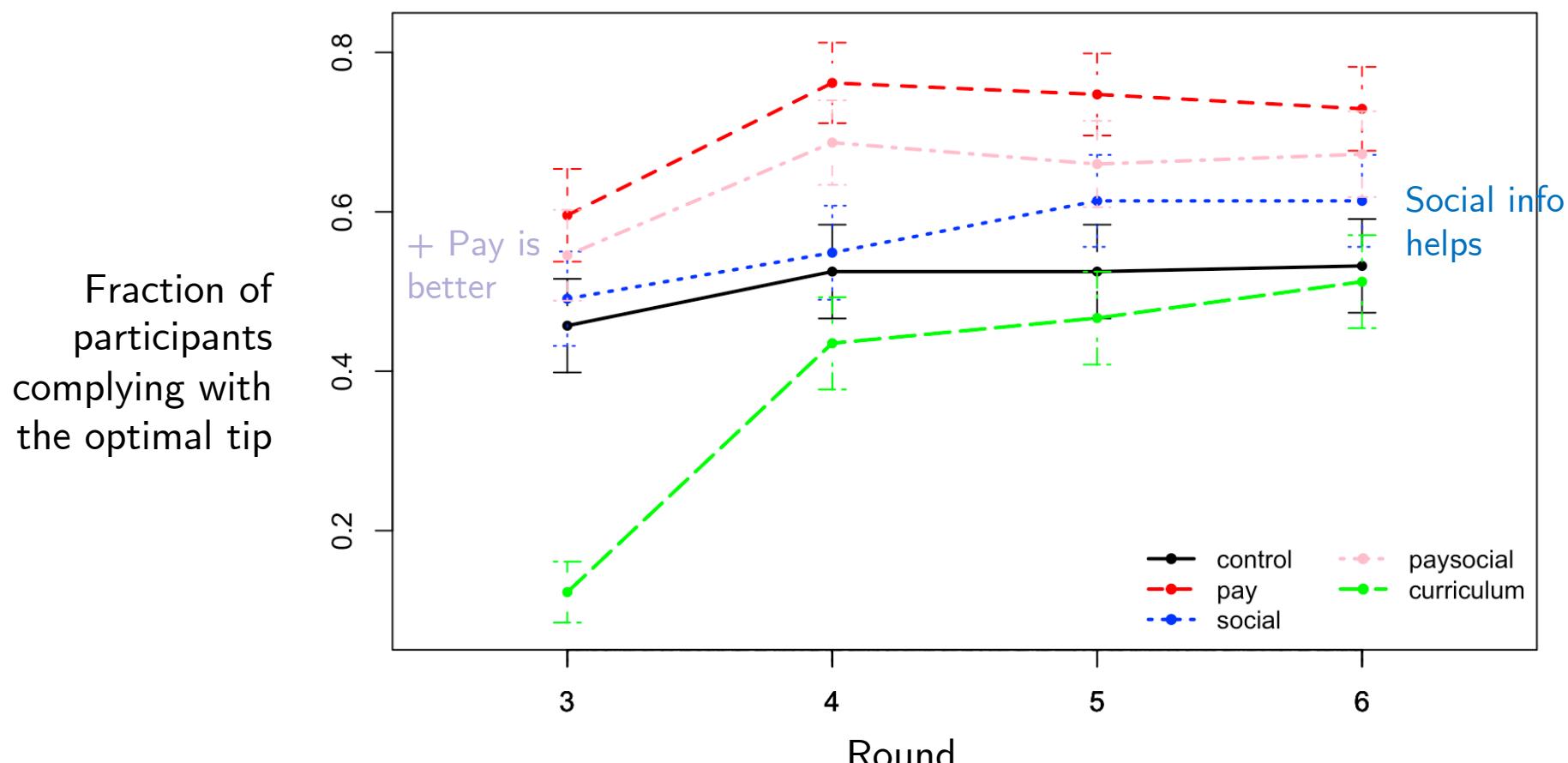
Improving Compliance

Interventions based on incentives, social information, and pace



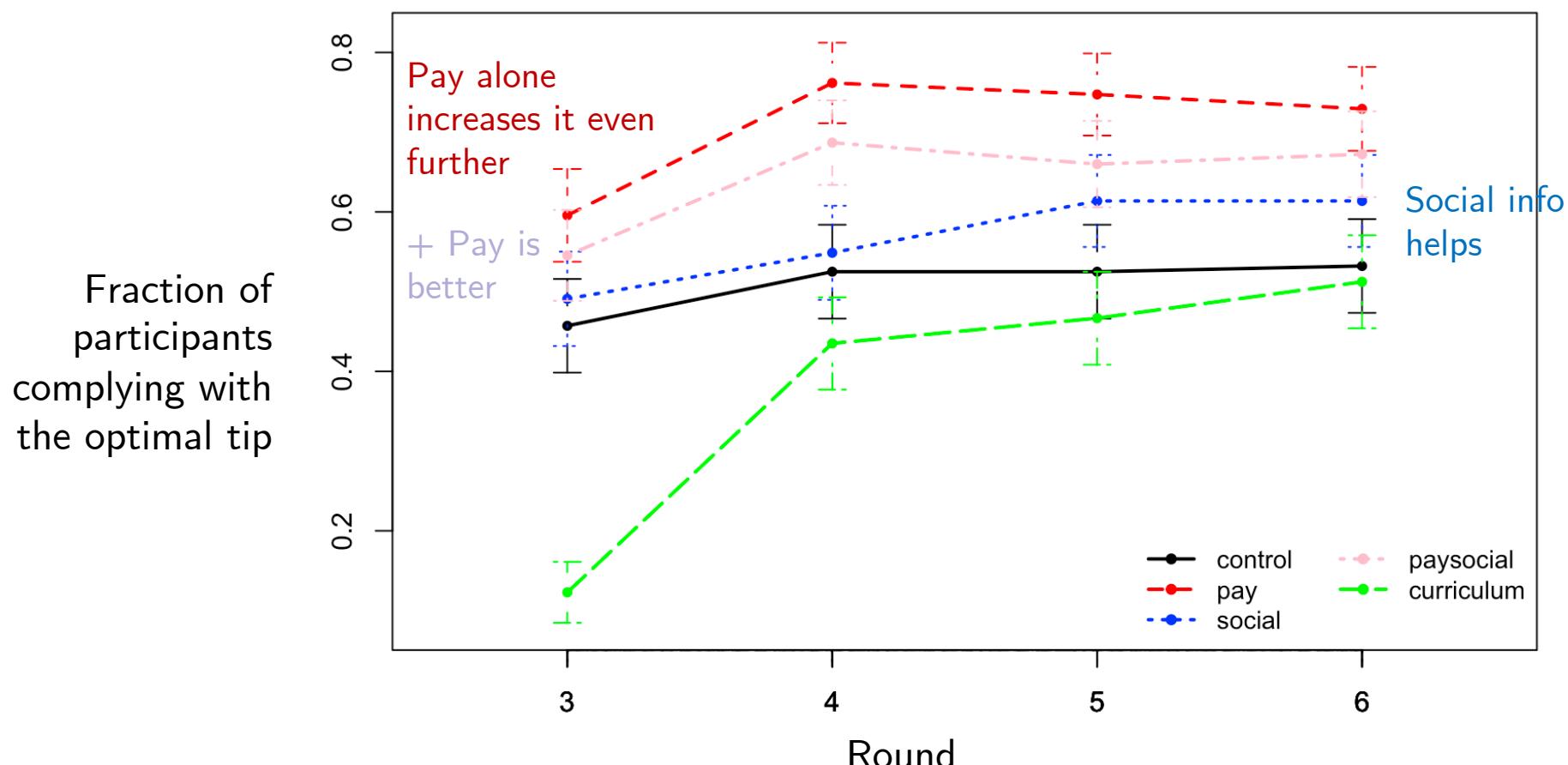
Improving Compliance

Interventions based on incentives, social information, and pace



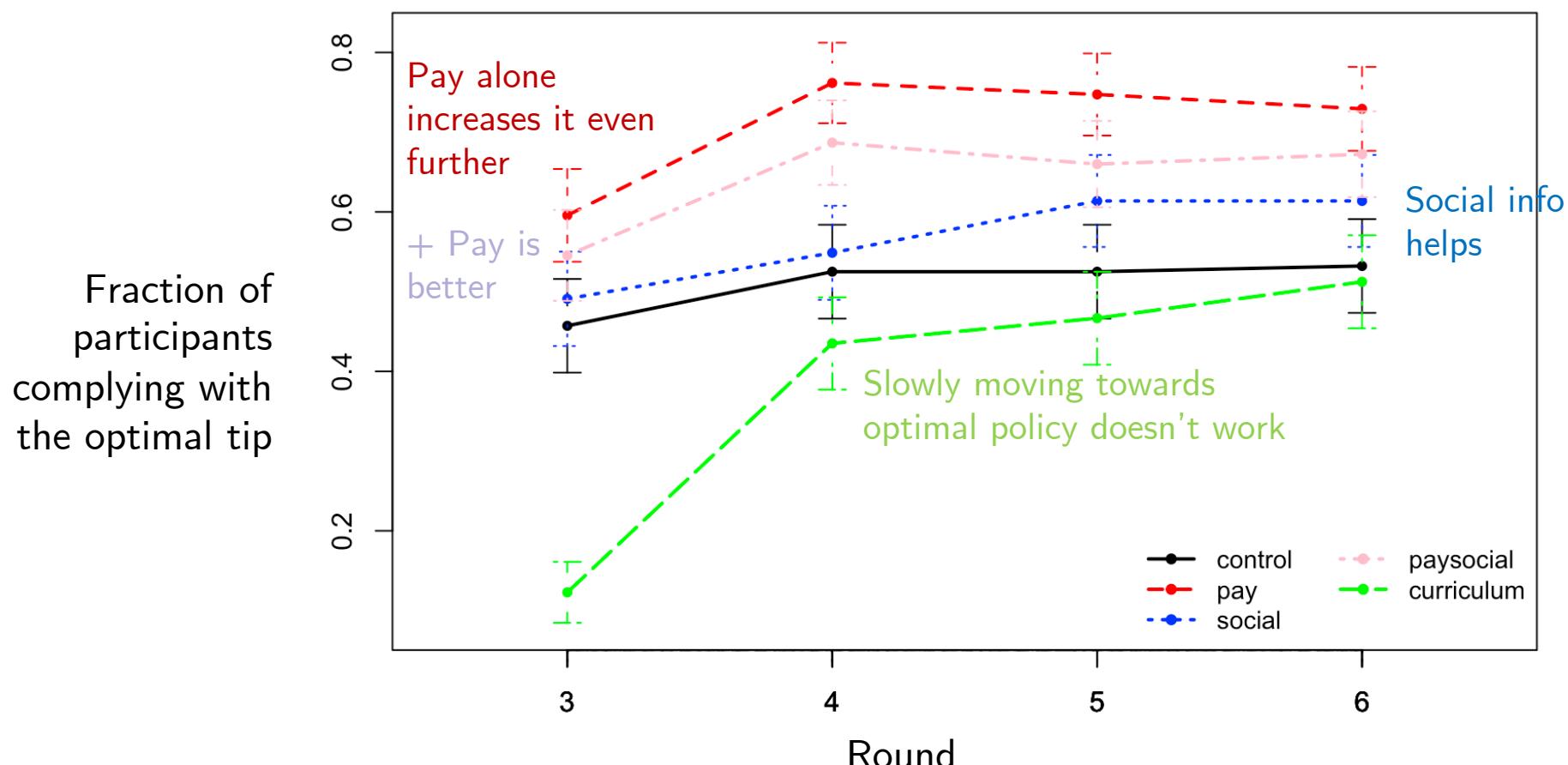
Improving Compliance

Interventions based on incentives, social information, and pace



Improving Compliance

Interventions based on incentives, social information, and pace



Study 1:

Quick Recap

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

with Hamsa Bastani & Osbert Bastani
Major Revision @ Management Science



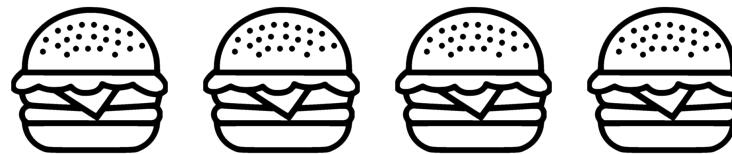
(Available at: bit.ly/tipspaper)

Study 1:

Quick Recap

w/o Experience = 0

Server



12 ticks to cook

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



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(Available at: bit.ly/tipspaper)

Study 1:

Quick Recap

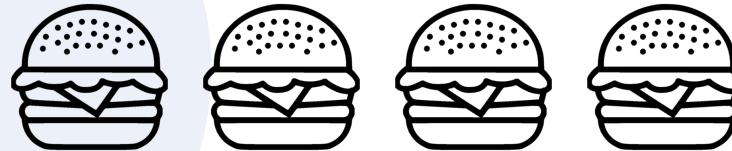
w/o Experience = 0

Server



12 ticks to cook

Intuitive = 1



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



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Major Revision @ Management Science

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Study 1:

Quick Recap

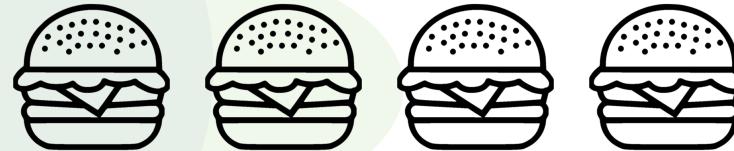
w/o Experience = 0

Server



12 ticks to cook

Intuitive = 1



Optimal = 2

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



with Hamsa Bastani & Osbert Bastani
Major Revision @ Management Science

(Available at: bit.ly/tipspaper)

Study 1:

Quick Recap

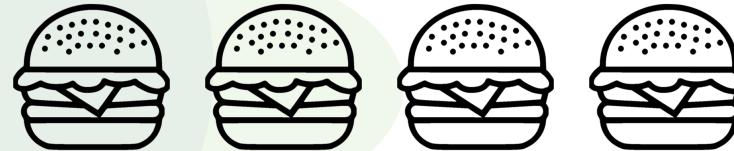
w/o Experience = 0

Server



12 ticks to cook

Intuitive = 1



Optimal = 2

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)

What If Decisions Are **Continuous**?

What If Decisions Are **Continuous?**

Also, What If Things Are Uncertain?

Study 2:

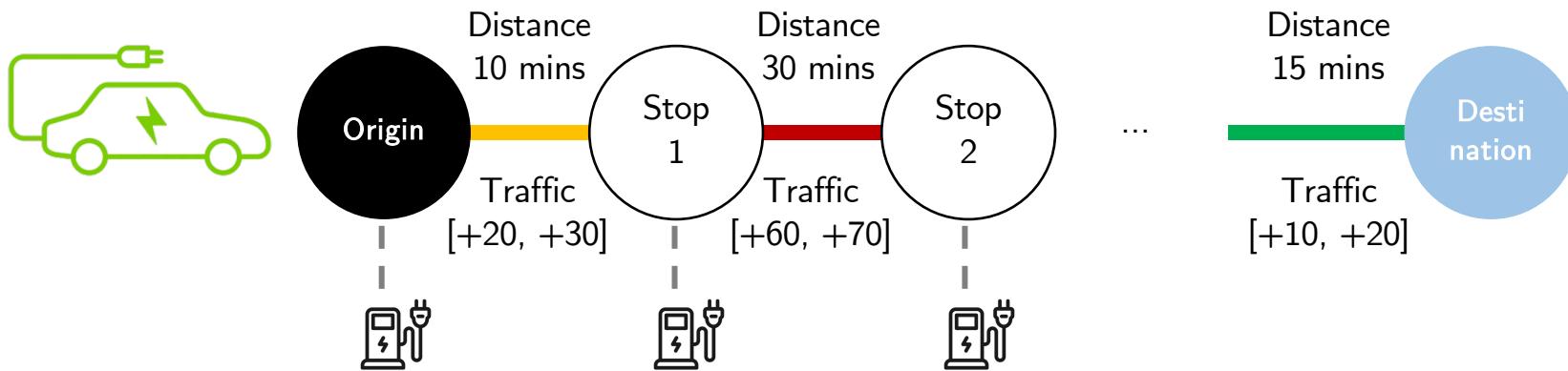
What If Decisions Are **Continuous?**

Also, What If Things Are Uncertain?

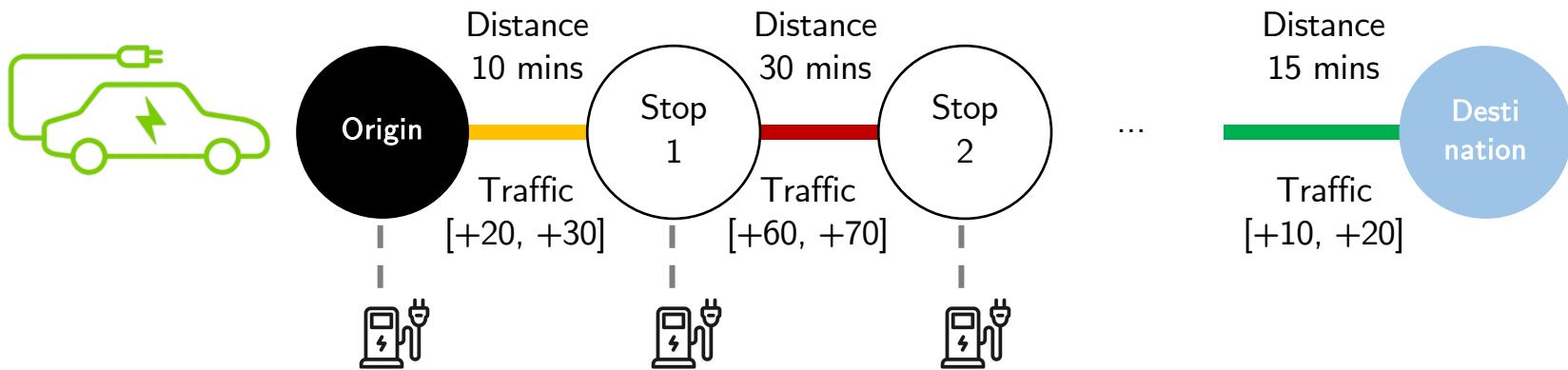


Study 2:

EV Charging Game

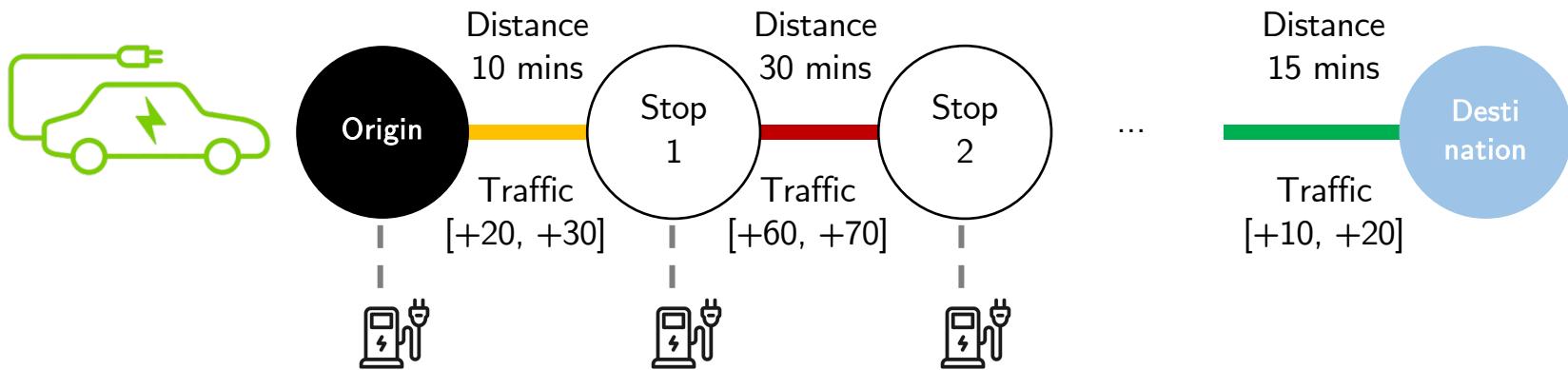


EV Charging Game



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

EV Charging Game

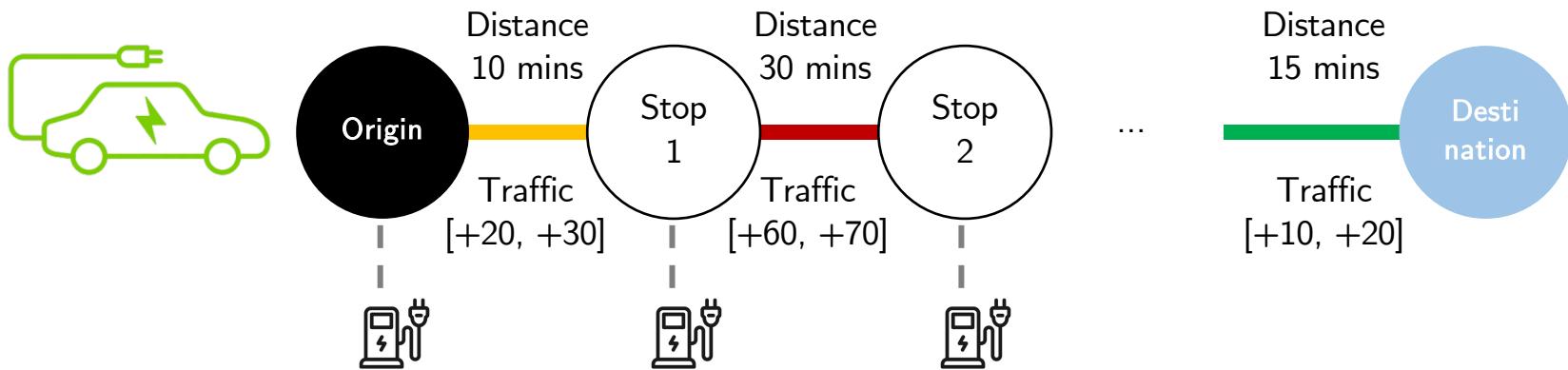


Goal: Get to destination as fast as possible (**1% charge can travel 1 minute**)

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

Study 2:

EV Charging Game

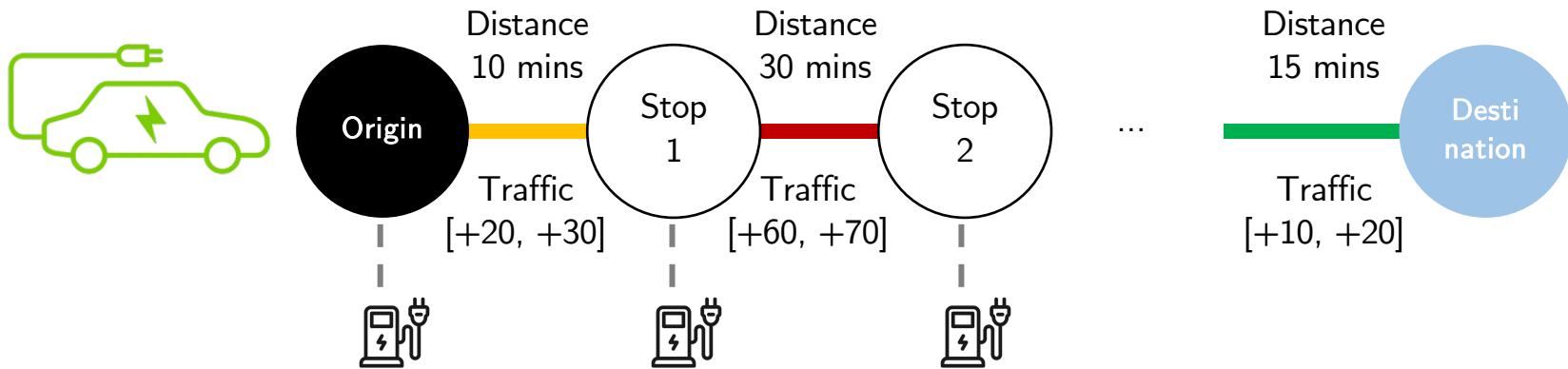


Goal: Get to destination as fast as possible (**1% charge can travel 1 minute**)

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

Study 2:

EV Charging Game

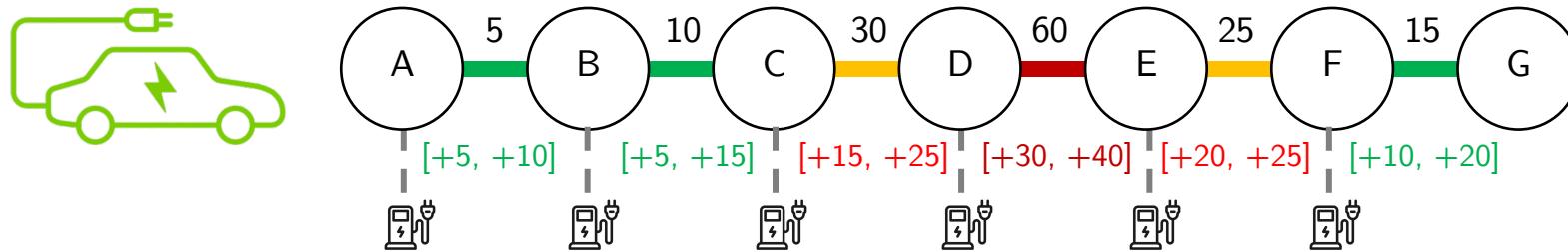


Goal: Get to destination as fast as possible (**1% charge can travel 1 minute**)

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

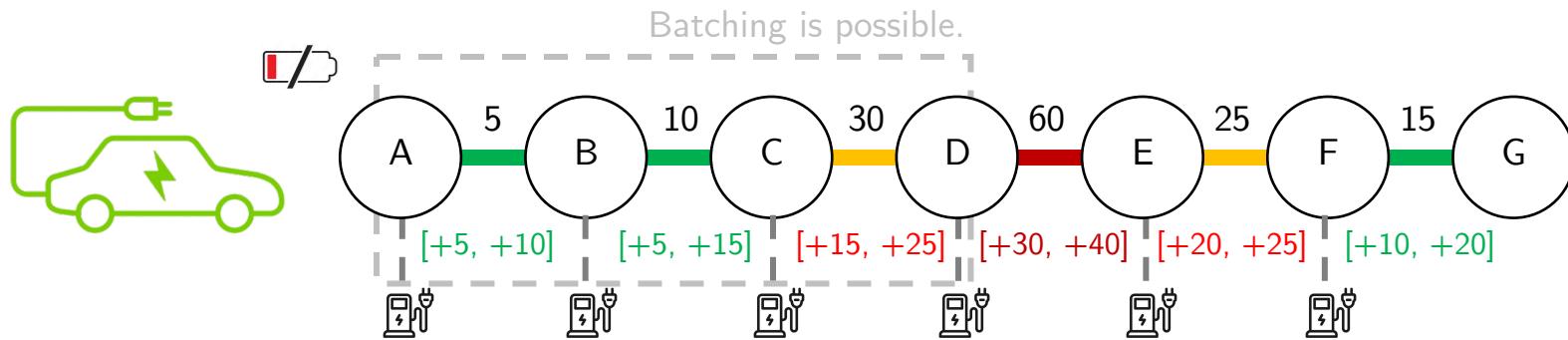
Study 2A:

Design To Batch, or Not to Batch



Study 2A:

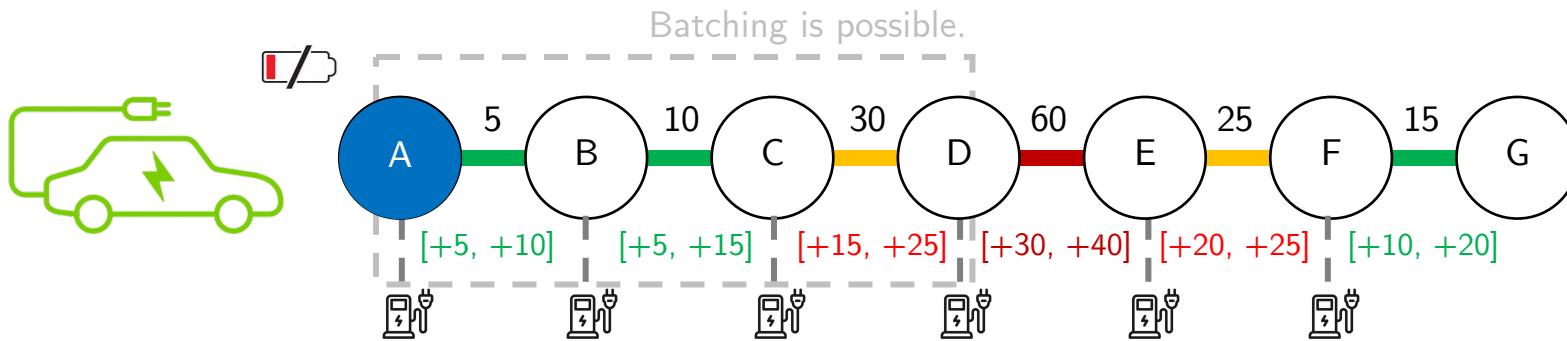
Design To Batch, or Not to Batch



Study 2A:

Design

To Batch, or Not to Batch

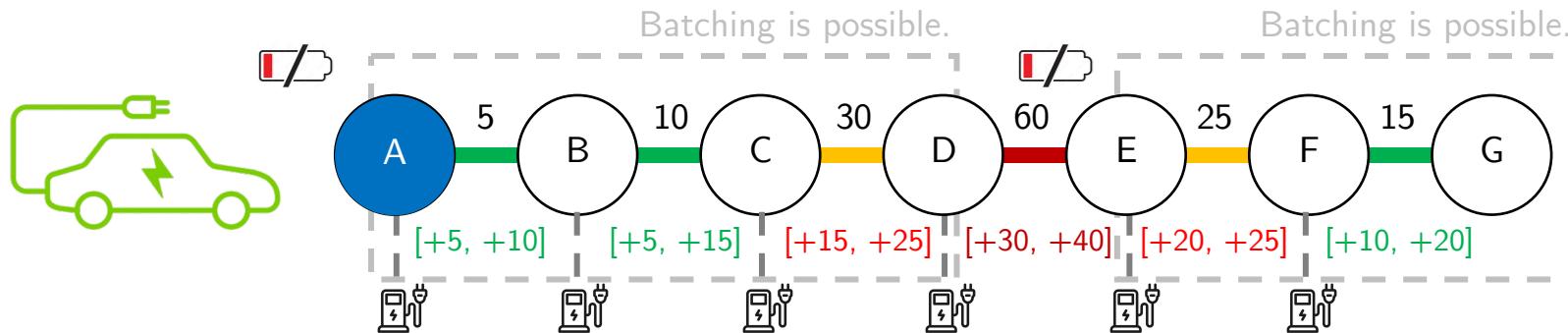


Optimal is to “batch” the required charges
for the next two stops ($A \rightarrow C$)
rather than just $A \rightarrow B$ or further batch $A \rightarrow D$.

Study 2A:

Design

To Batch, or Not to Batch

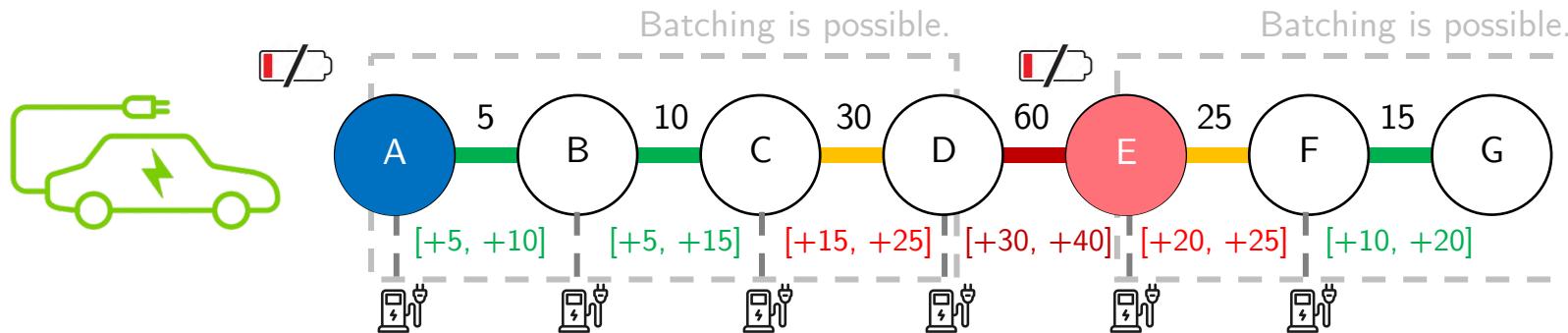


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Study 2A:

Design

To Batch, or Not to Batch



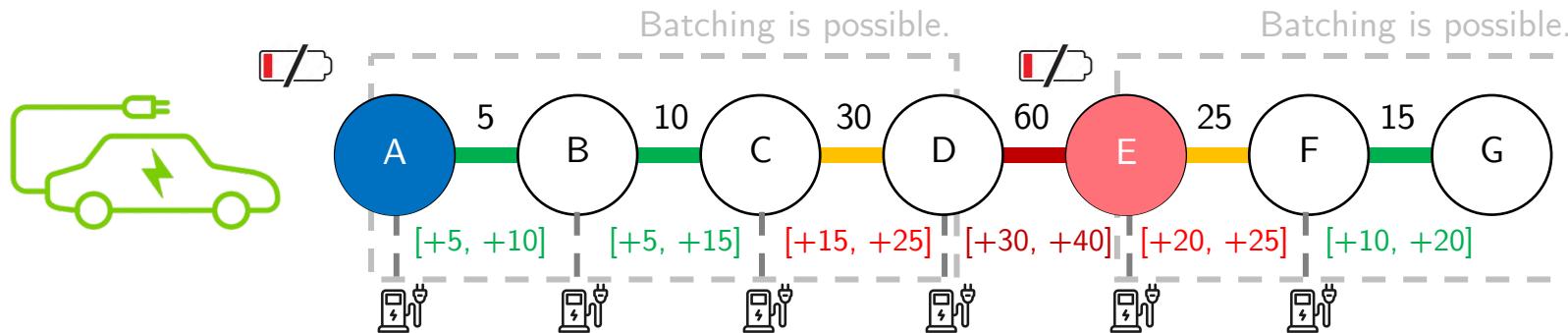
Optimal is to “batch” the required charges for the next two stops ($A \rightarrow C$) rather than just $A \rightarrow B$ or further batch $A \rightarrow D$.



Optimal is to “split” = only charge for the next stop ($E \rightarrow F$) rather than batch $E \rightarrow G$.

Study 2A:

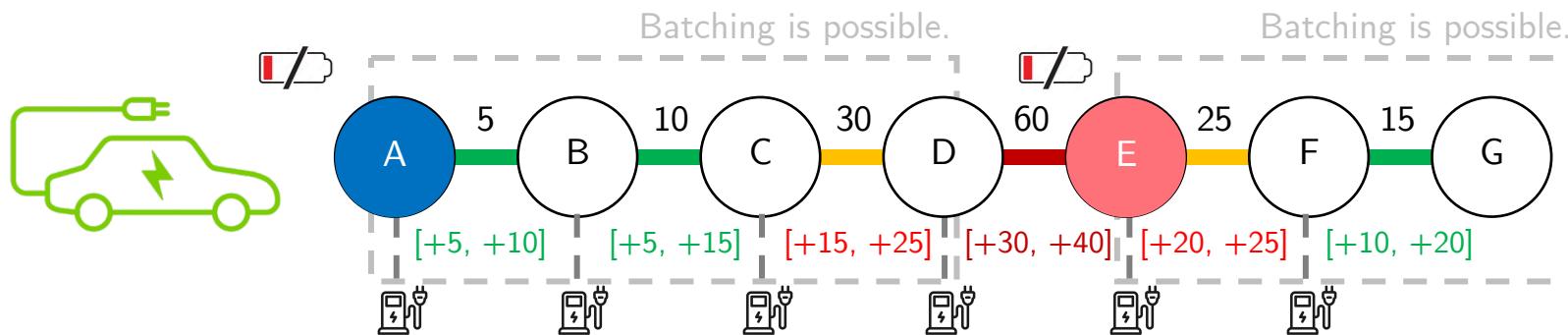
Design Flow



Performance: Time to destination

Study 2A:

Design Flow



Performance: Time to destination

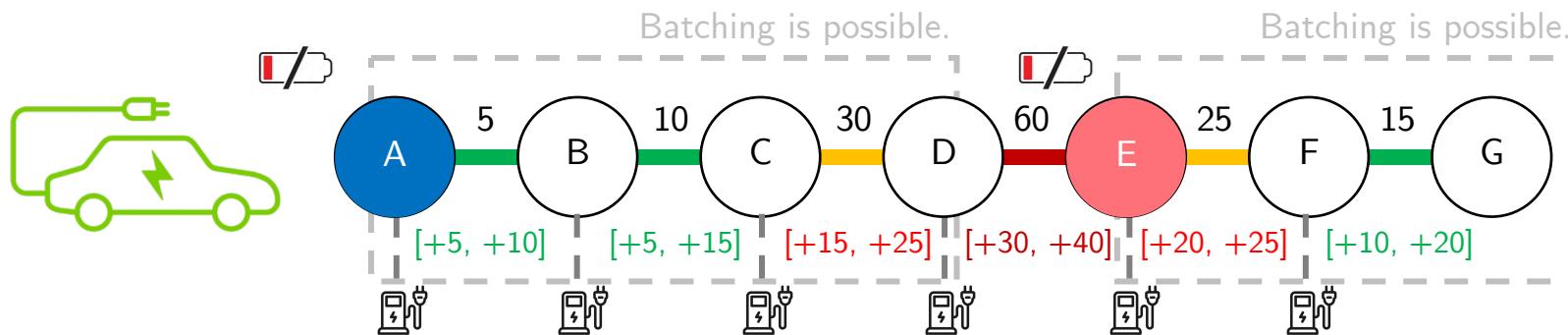
Round 1

Round 2

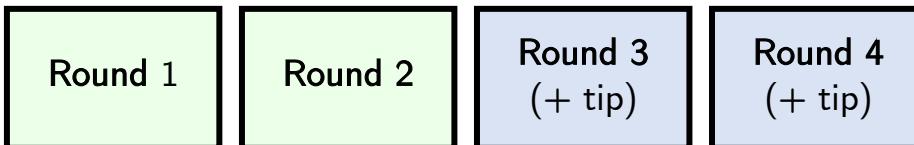
Realized traffic will be different across rounds but drawn from the same distributions

Study 2A:

Design Flow



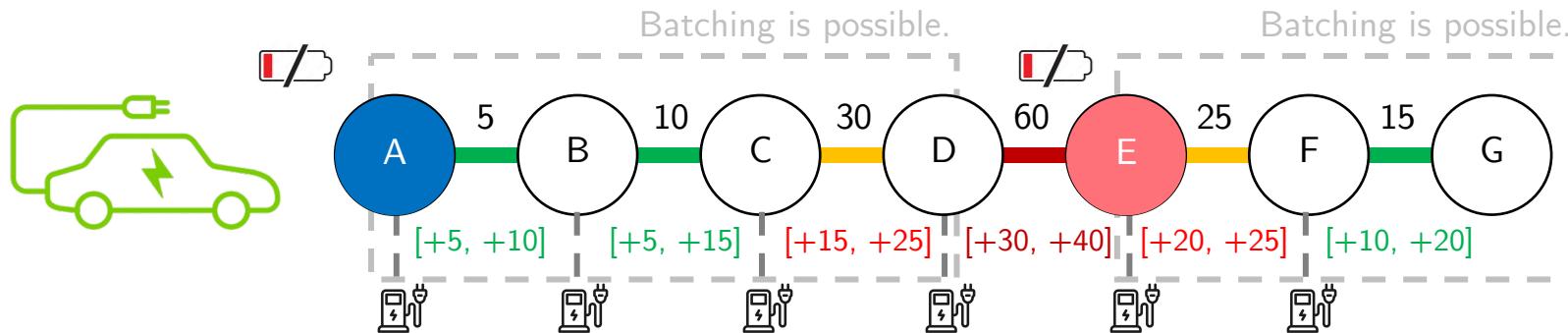
Performance: Time to destination



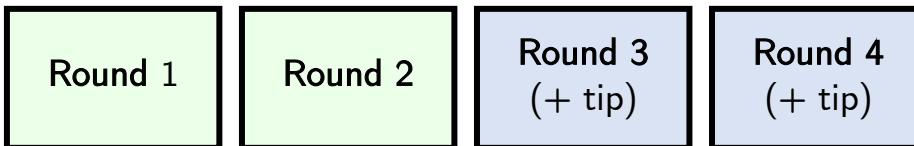
Realized traffic will be different across rounds but drawn from the same distributions

Study 2A:

Design Tip Conditions



Performance: Time to destination



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

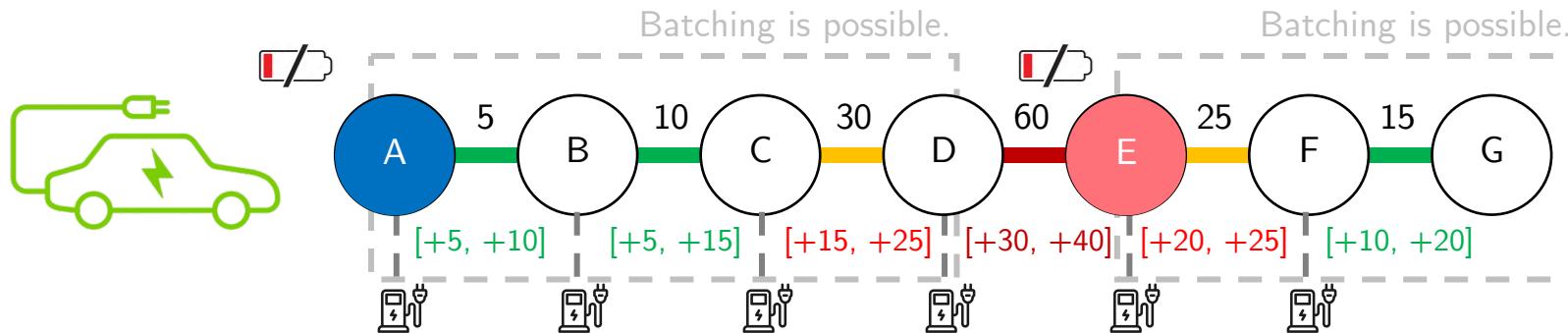
At every stop, we present either...

Precise Tip:

You should exit and charge X%

Study 2A:

Design Tip Conditions



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:

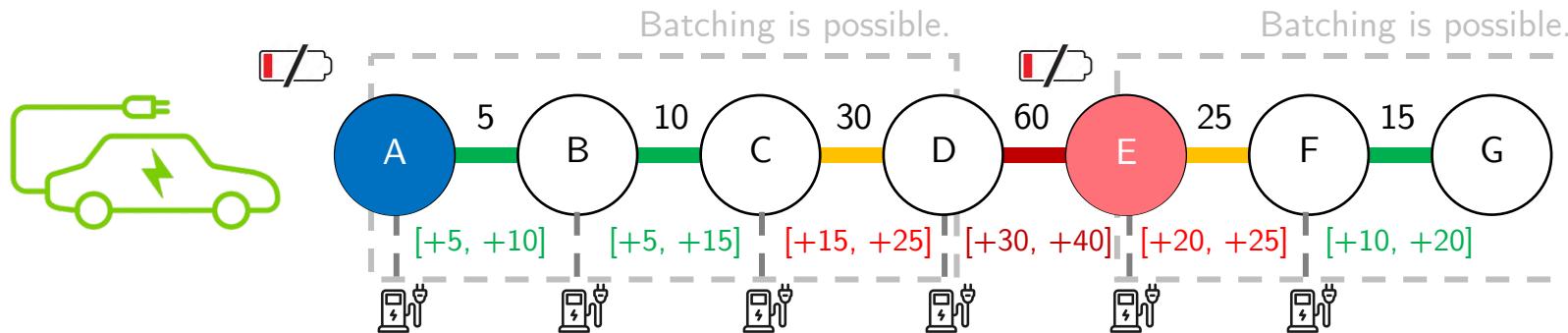
You should exit and charge X%

Broad Tip:

"Split" You should charge enough for this segment

Study 2A:

Design Tip Conditions



Performance: Time to destination



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

At every stop, we present either...

Precise Tip:

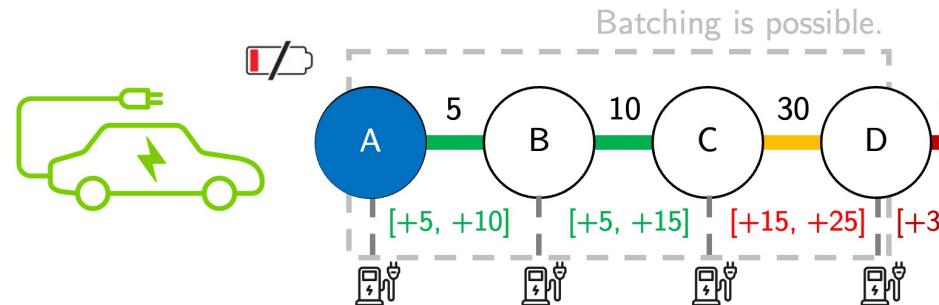
You should exit and charge X%

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)

Aftercharge

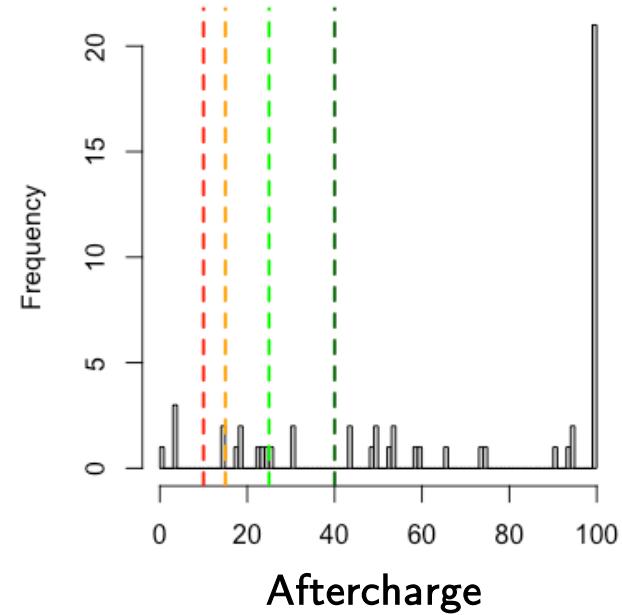
= amount of charge after re-charging

Study 2A:

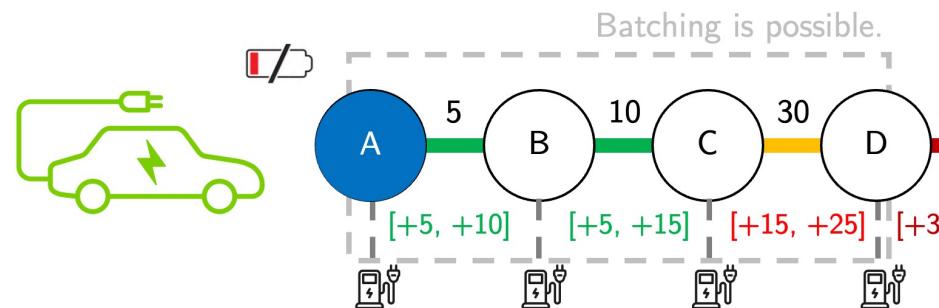
Results

Wide Range of Decisions

Round 1



= amount of charge after re-charging

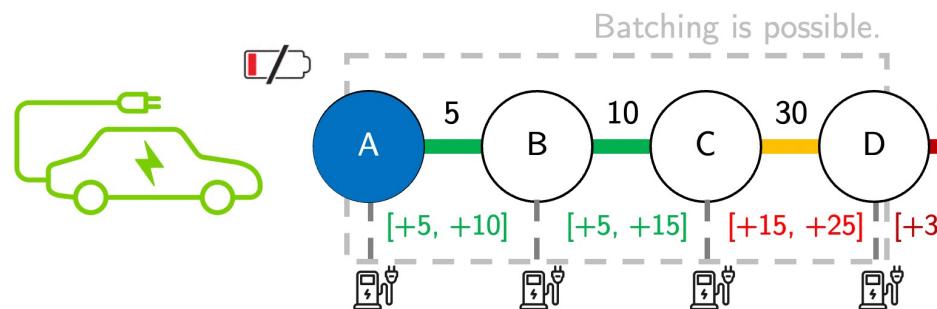
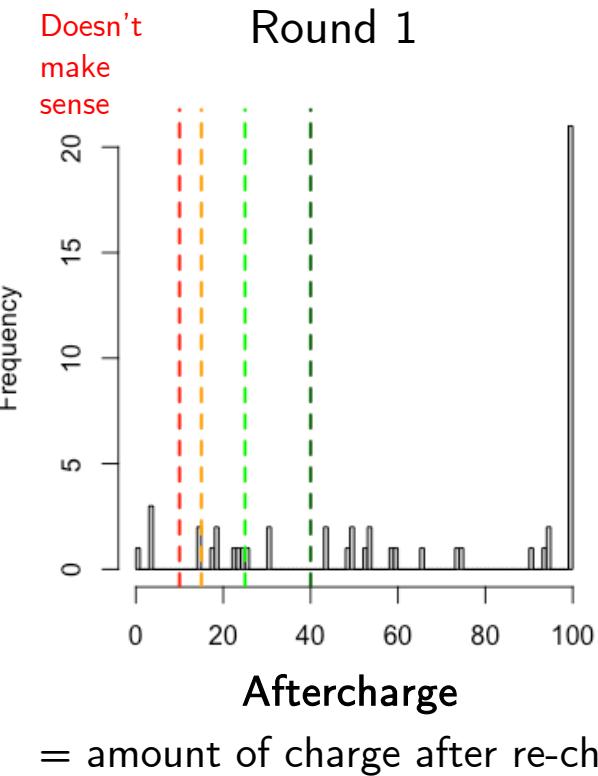


Exit A: Forced to charge
Optimal: Batch A → C
rather than just A → B
or further batch A → D.
("aftercharge" = 25-40)

Study 2A:

Results

Wide Range of Decisions

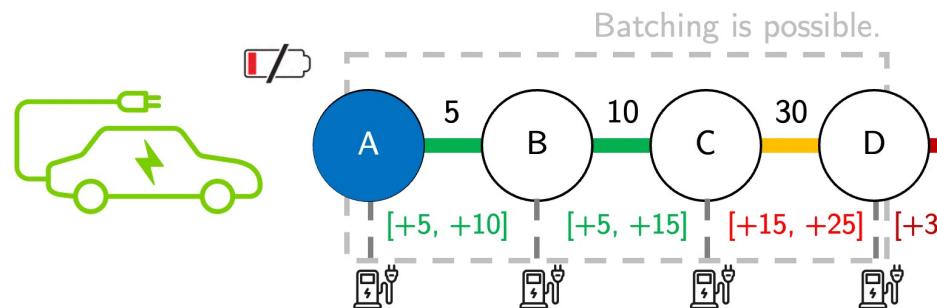
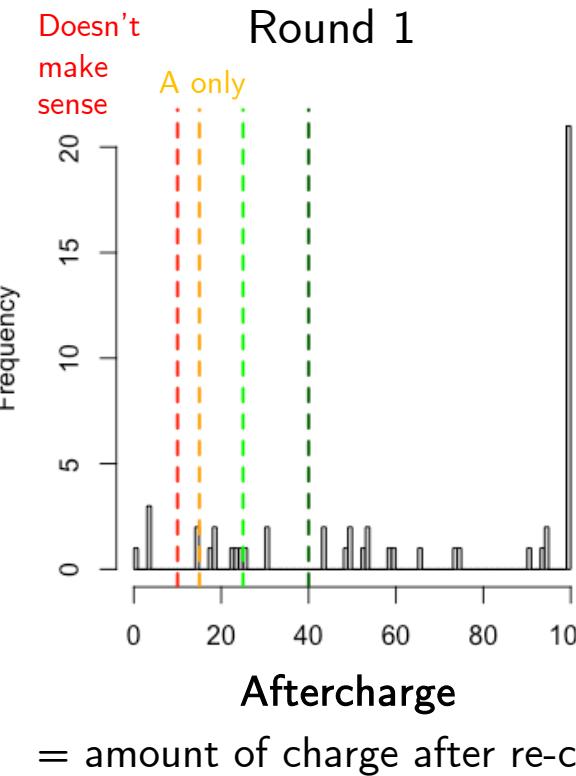


Exit A: Forced to charge
Optimal: Batch A → C
rather than just A→B
or further batch A→D.
(“aftercharge” = 25-40)

Study 2A:

Results

Wide Range of Decisions

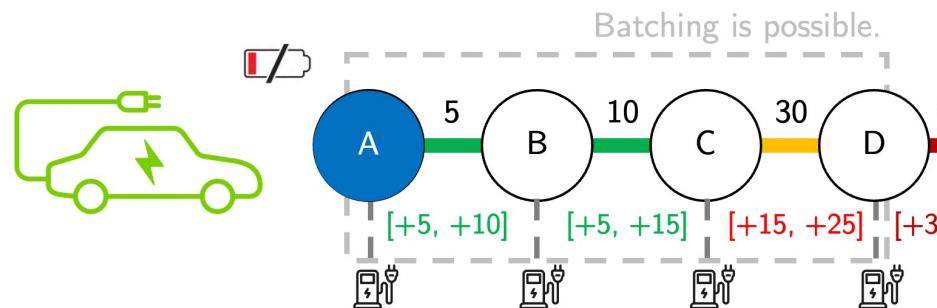
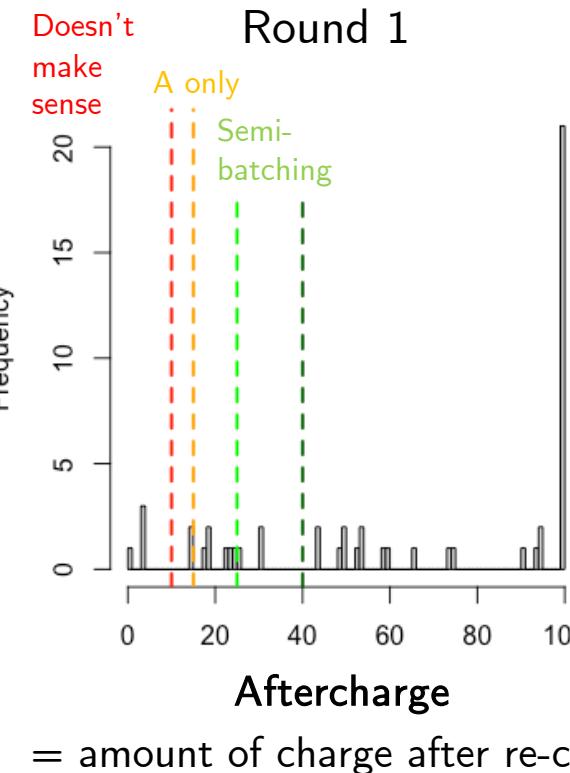


Exit A: Forced to charge
Optimal: Batch A → C
rather than just A → B
or further batch A → D.
("aftercharge" = 25-40)

Study 2A:

Results

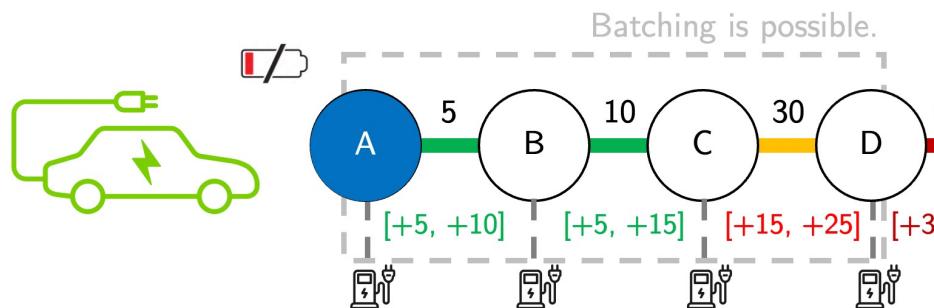
Wide Range of Decisions



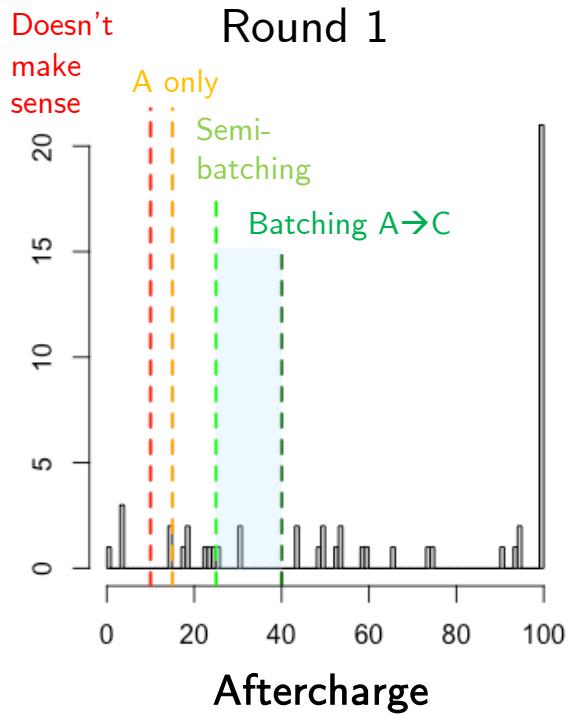
Exit A: Forced to charge
Optimal: Batch A → C
rather than just A → B
or further batch A → D.
("aftercharge" = 25-40)

Results

Wide Range of Decisions



Round 1



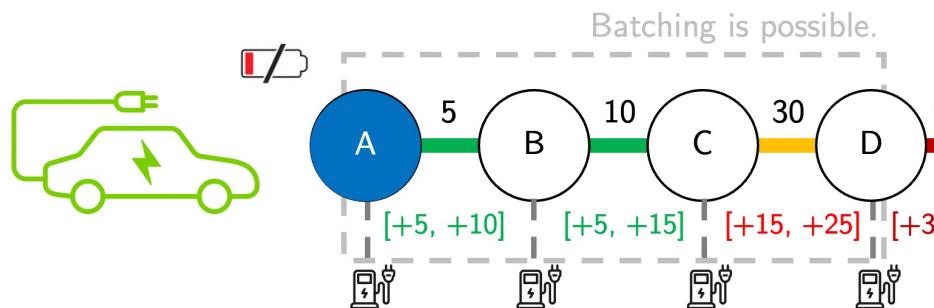
= amount of charge after re-charging

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

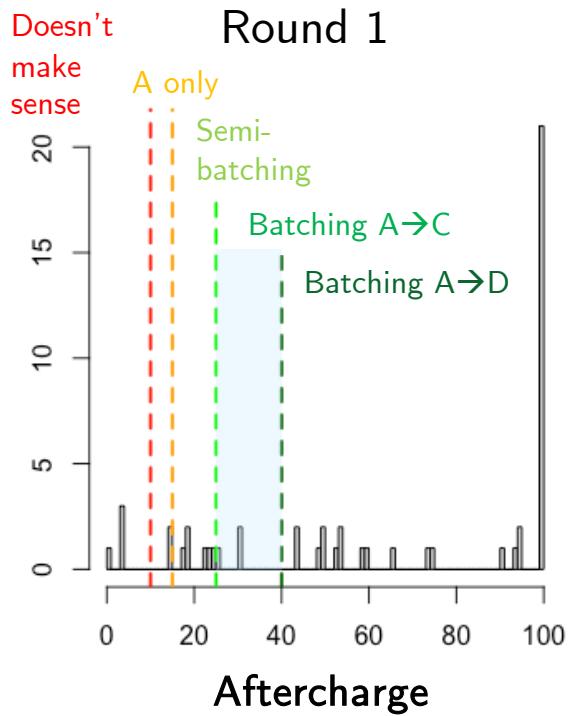
Study 2A:

Results

Wide Range of Decisions



Round 1

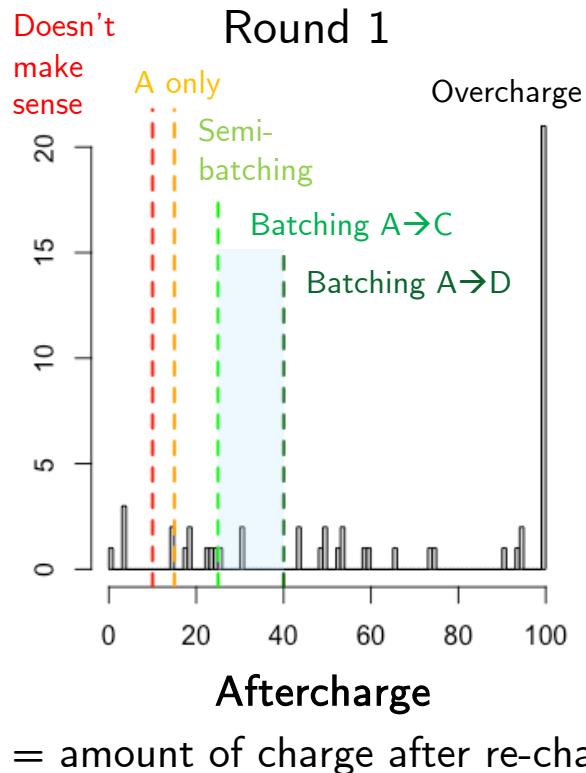
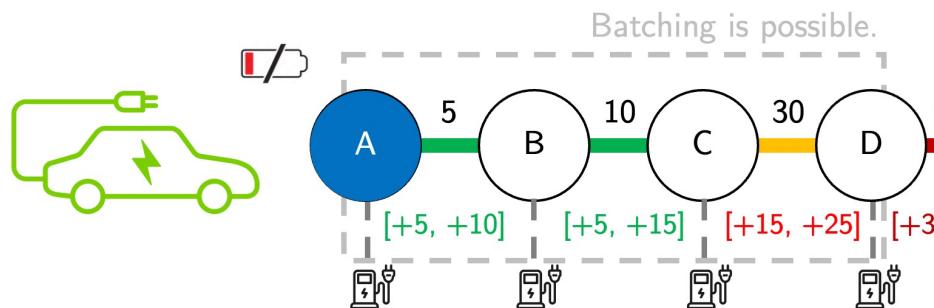


= amount of charge after re-charging

Study 2A:

Results

Wide Range of Decisions

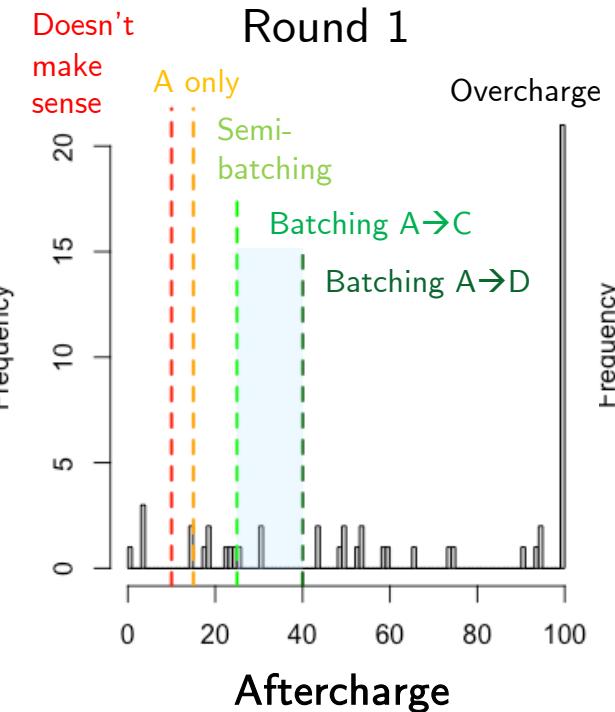


Exit A: Forced to charge
Optimal: Batch A → C
rather than just A→B
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("aftercharge" = 25-40)

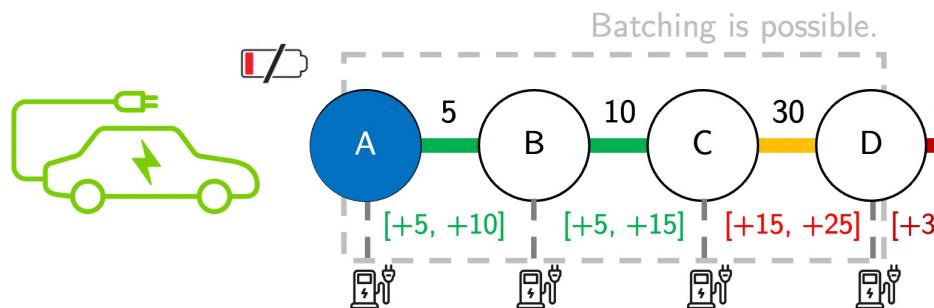
Study 2A:

Results

People Learned w/o Tip



= amount of charge after re-charging

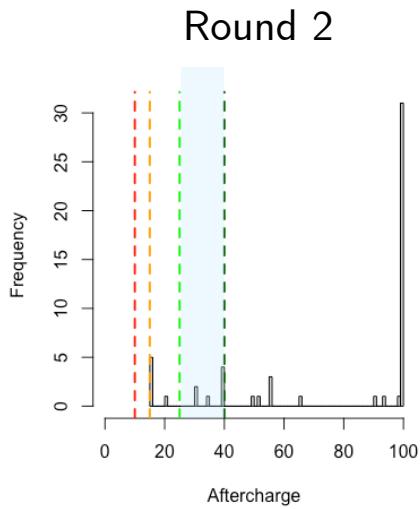


Exit A: Forced to charge
Optimal: Batch A → C
rather than just A→B
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("aftercharge" = 25-40)

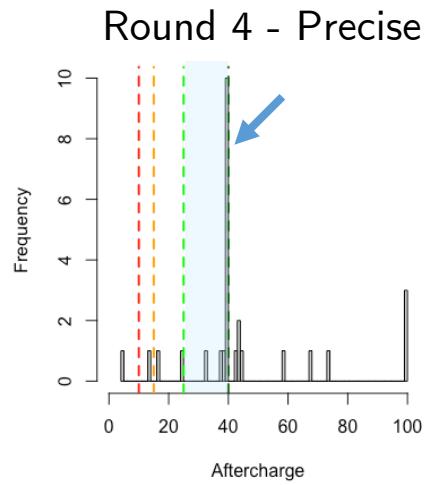
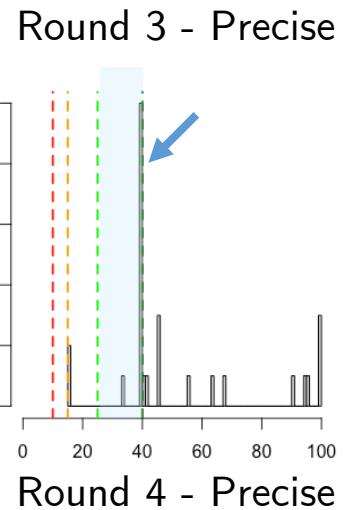
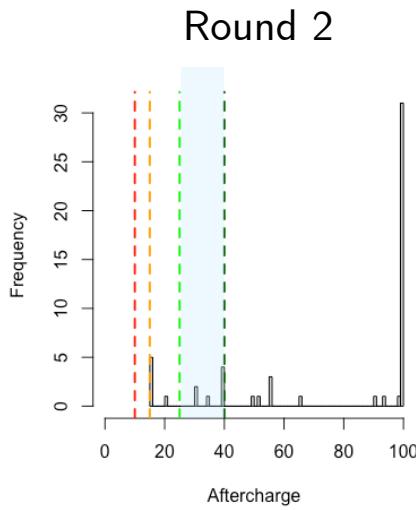
In one round, everyone learned to do at least semi-batching for this exit.

Results

What Happened After Tip?

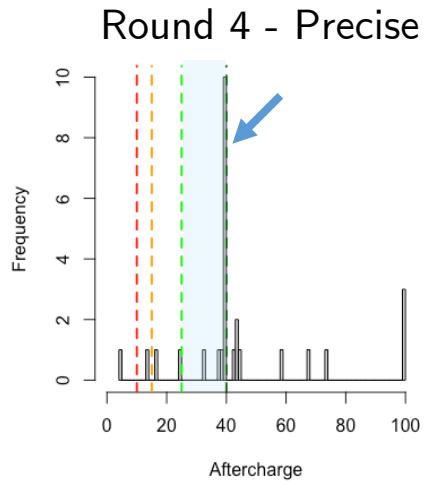
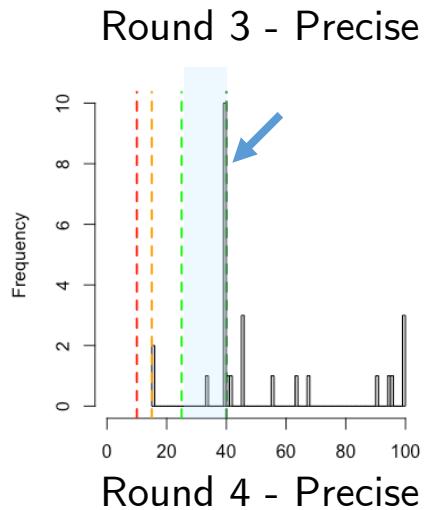
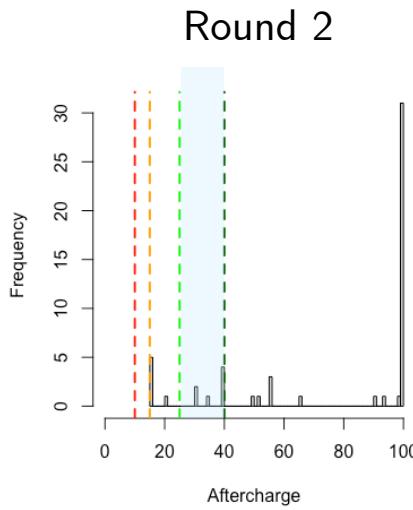


Results



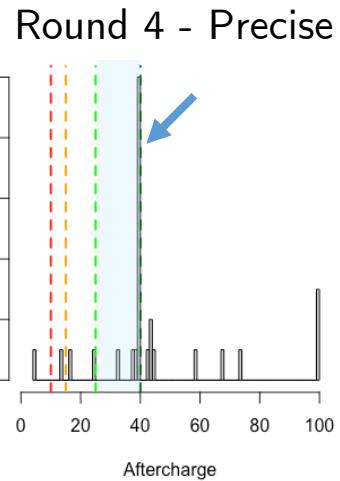
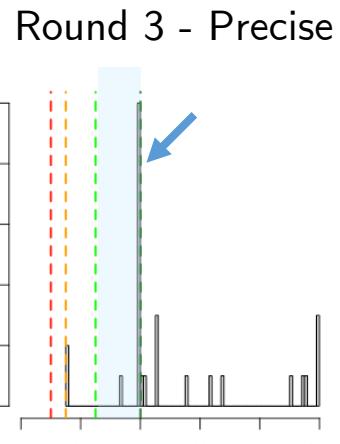
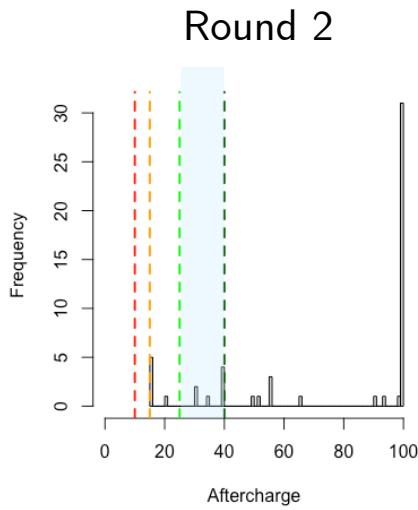
Results

Precise Tip Worked (as Expected)



The Precise tip
successfully nudged
participants to
batch A → C

Results

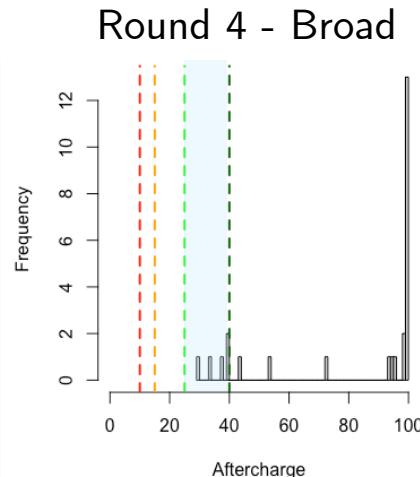
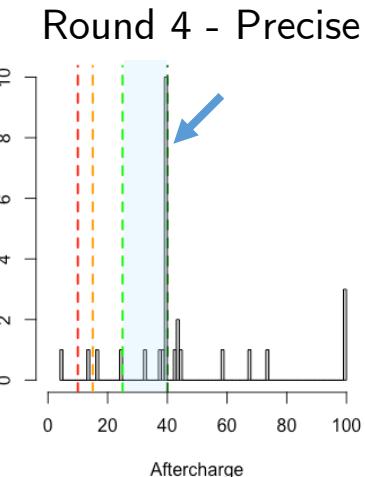
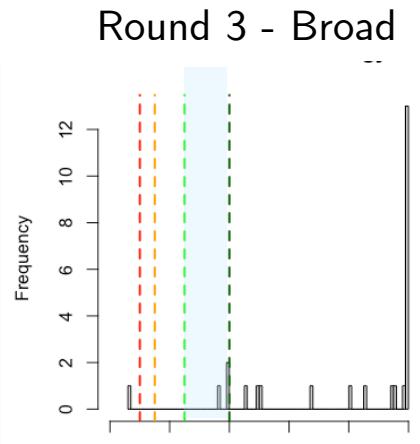
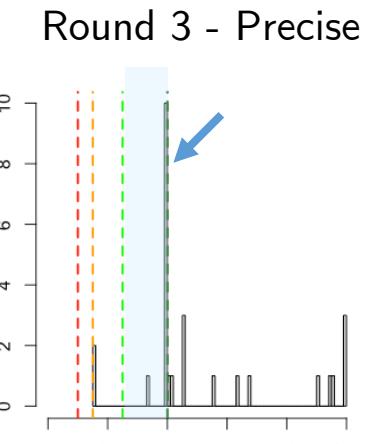
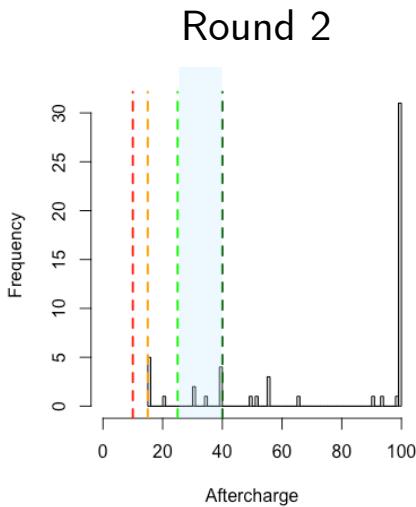


The Precise tip
successfully nudged
participants to
batch A → C

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

Results

Broad Tip Kind of Failed



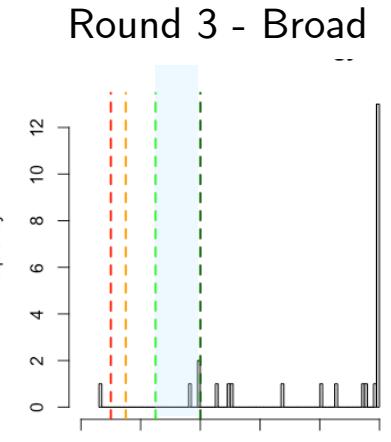
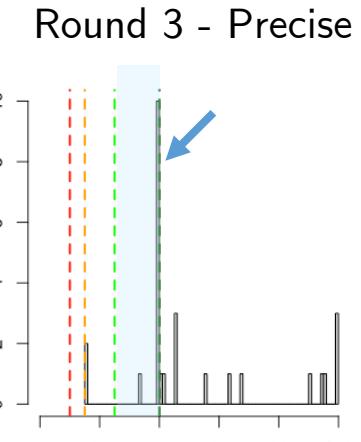
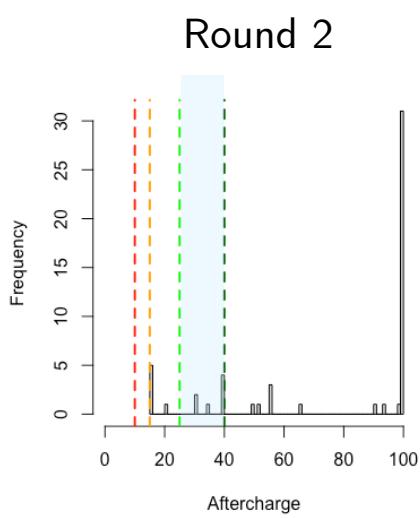
The Precise tip successfully nudged participants to batch A → C

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

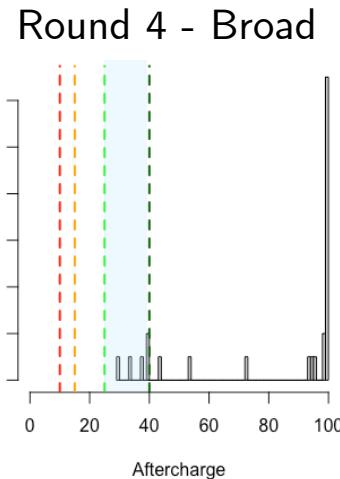
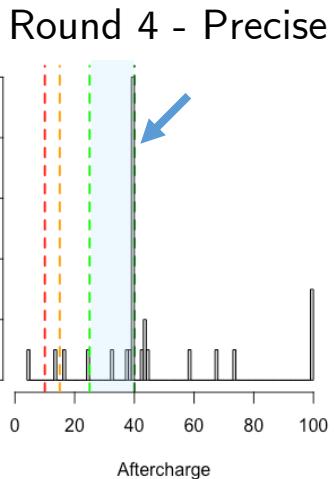
The Broad tip had low compliance even though it was clear what the participant should do

Results

Broad Tip Kind of Failed



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



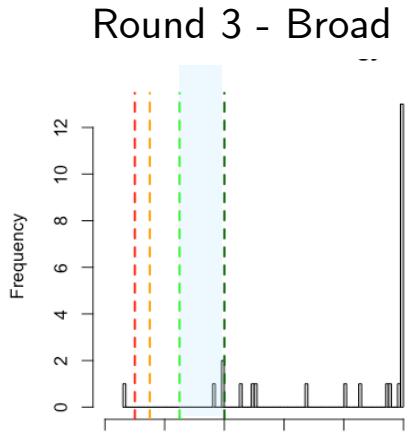
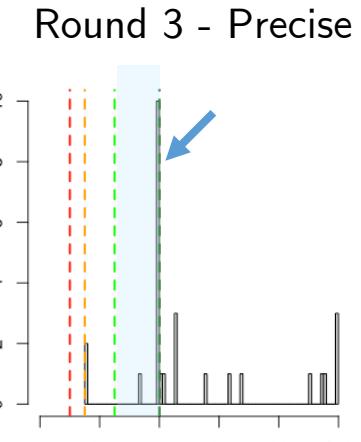
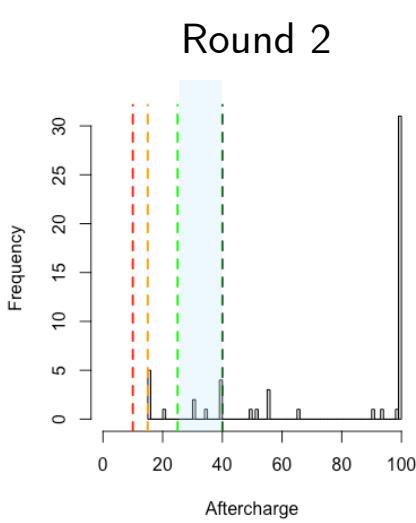
The **Precise** tip
successfully nudged
participants to
batch A → C

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

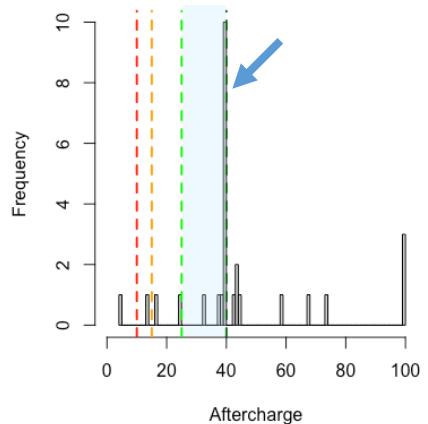
Q: Could it be due to
the advice being
perceived as
counterintuitive?

Results

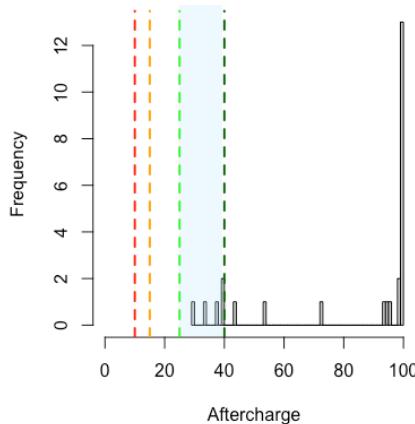
Broad Tip Kind of Failed



Round 4 - Precise



Round 4 - Broad



The Precise tip successfully nudged participants to batch A → C

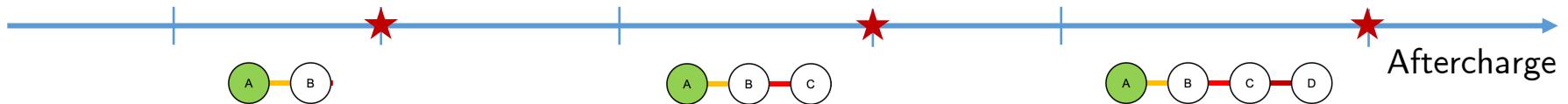
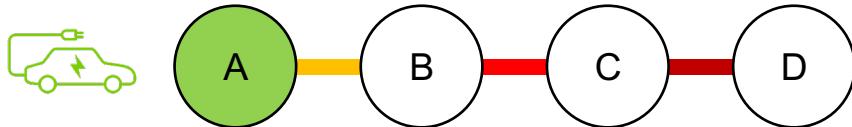
Broad tip
“You should charge enough for this segment and the next one”

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

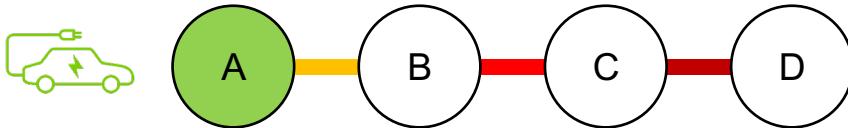
Q: Could it be due to the advice being perceived as counterintuitive?

Q: Did Precise tip help people learn?

Classifying Decisions



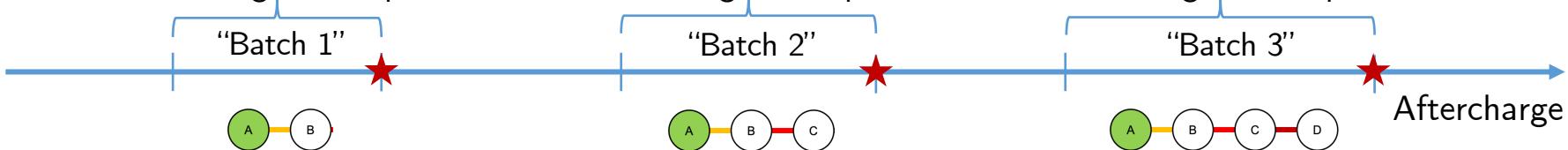
Classifying Decisions



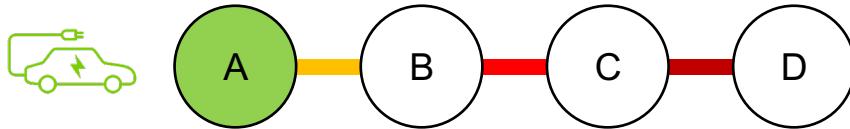
“Reasonable” levels:
pos. probability of
reaching next stop

“Reasonable” levels:
pos. probability of
reaching two stops

“Reasonable” levels:
pos. probability of
reaching three stops



Classifying Decisions



“Reasonable” levels:
pos. probability of
reaching next stop

“Batch 1”



“Reasonable” levels:
pos. probability of
reaching two stops

“Batch 2”



“Reasonable” levels:
pos. probability of
reaching three stops

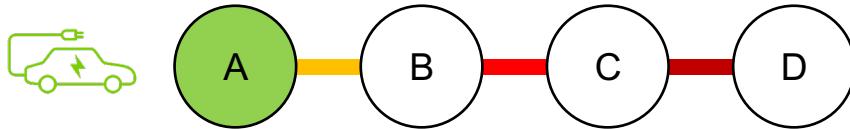
“Batch 3”



Aftercharge

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

Classifying Decisions



“Reasonable” levels:
pos. probability of
reaching next stop

“Batch 1”



“Reasonable” levels:
pos. probability of
reaching two stops

“Batch 2”



“Reasonable” levels:
pos. probability of
reaching three stops

“Batch 3”



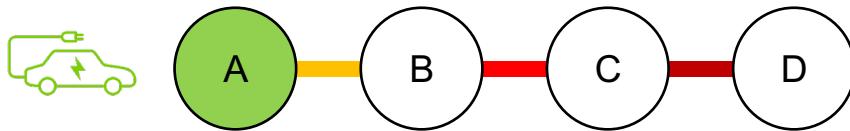
Aftercharge

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(risk aversion, limited look-ahead)
→ unnecessarily conservative

Hierarchical model of decision-making:

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

Classifying Decisions



“Reasonable” levels:
pos. probability of
reaching next stop

“Batch 1”



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

“Reasonable” levels:
pos. probability of
reaching two stops

“Batch 2”



“Reasonable” levels:
pos. probability of
reaching three stops

“Batch 3”



Aftercharge

Hierarchical model of decision-making:
1. Choice of broad interval
2. Choice of charge within interval

“out”

“below”

“in”

“above”

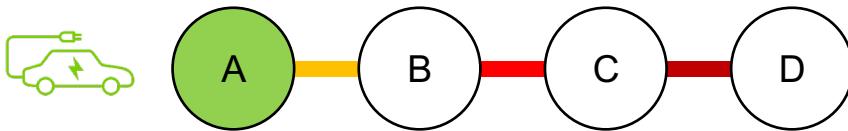
“Batch 1”

“Batch 2”

“Batch 3”

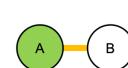
Aftercharge

Classifying Decisions



“Reasonable” levels:
pos. probability of
reaching next stop

“Batch 1”



“Reasonable” levels:
pos. probability of
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“Reasonable” levels:
pos. probability of
reaching three stops

“Batch 3”



Aftercharge

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Hierarchical model of decision-making:
1. Choice of broad interval
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“Batch 1”

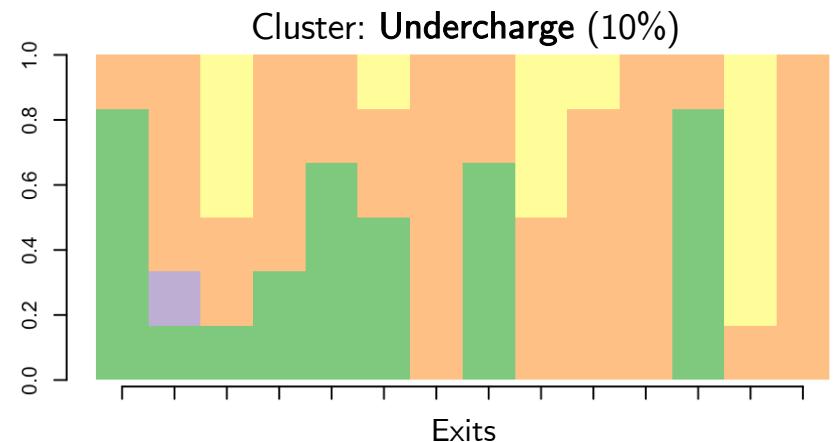
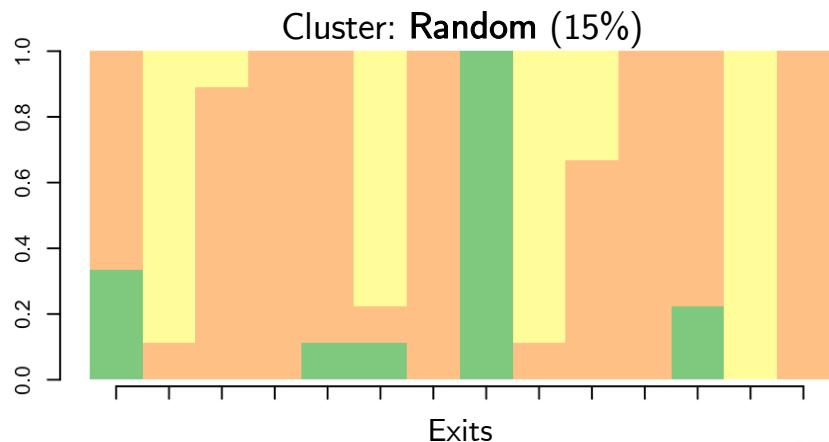
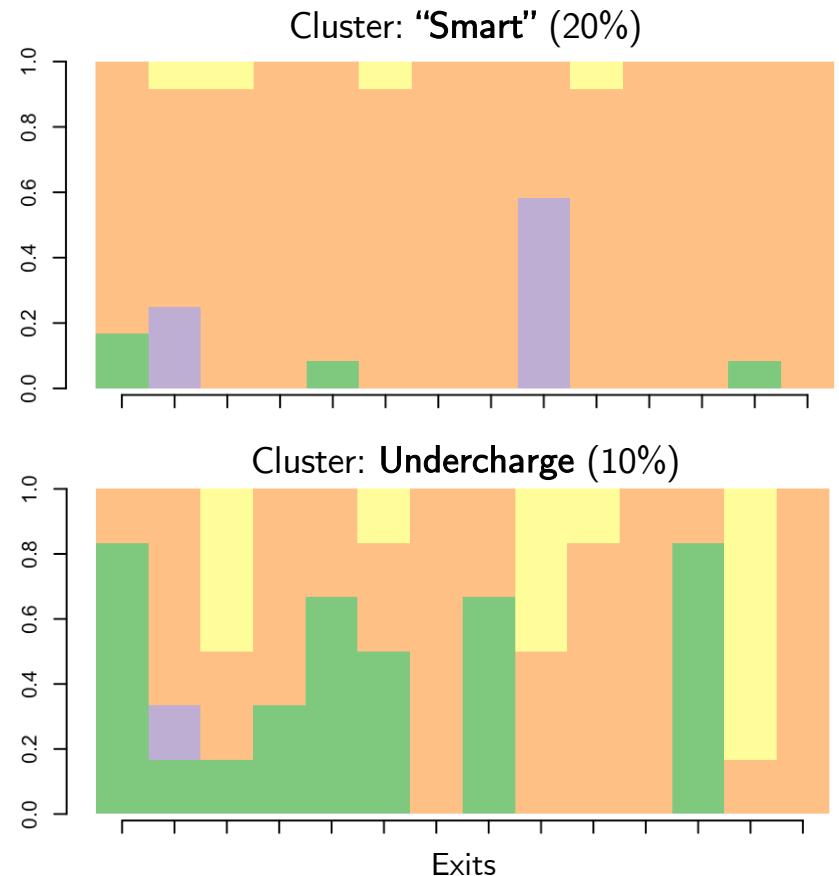
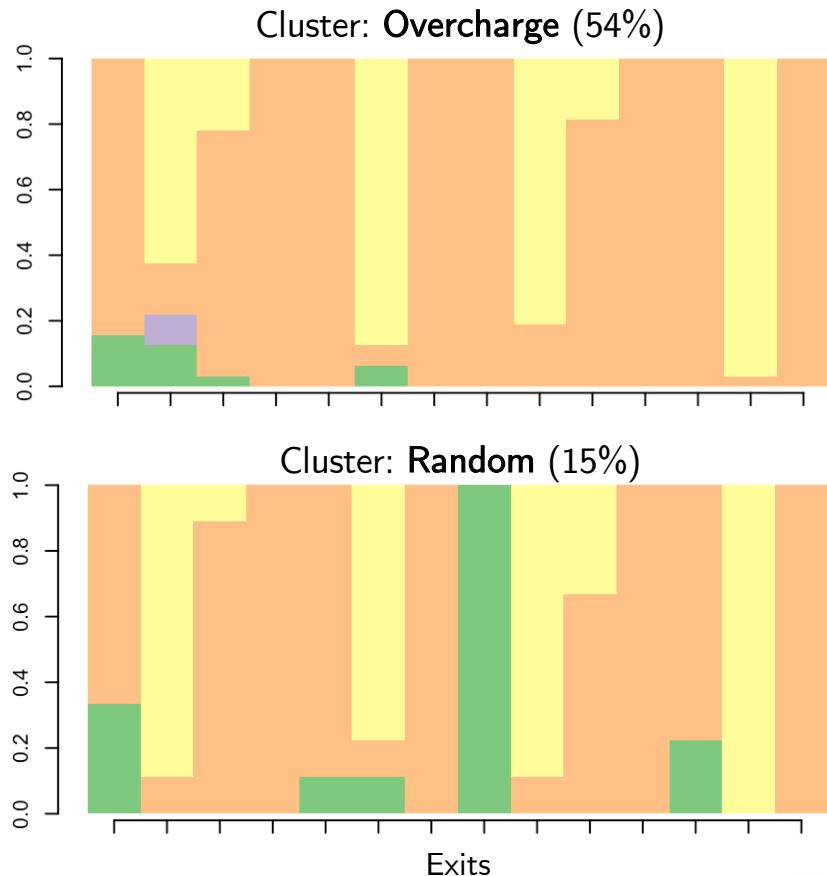
“Batch 2”

“Batch 3”

Aftercharge

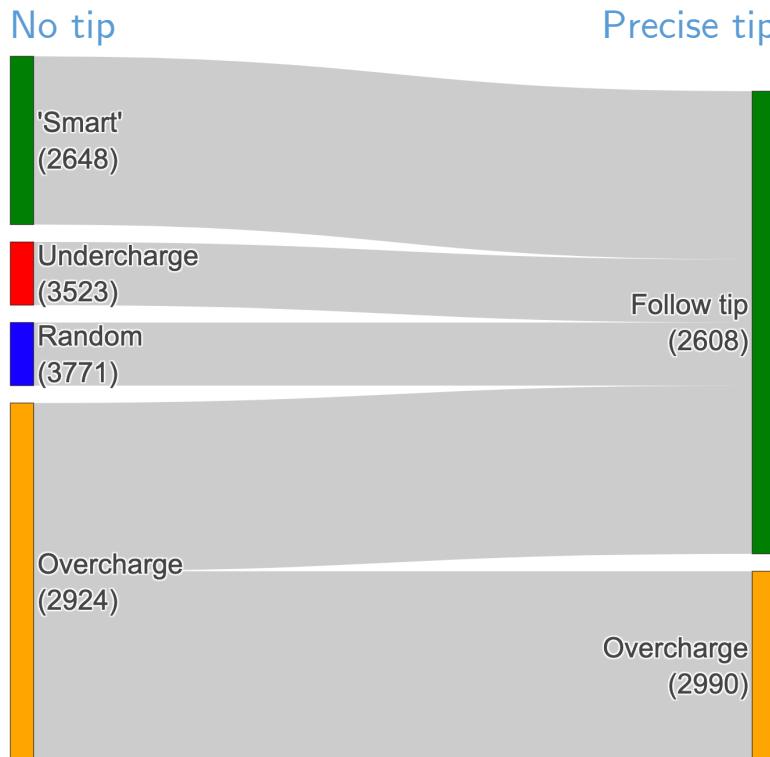
→ Consistent choice of intervals as an indicator of strategic behavior

Study 2A: Results Clustering Pre-Tip Behaviors



- Out
- Below
- In = optimal
- Above

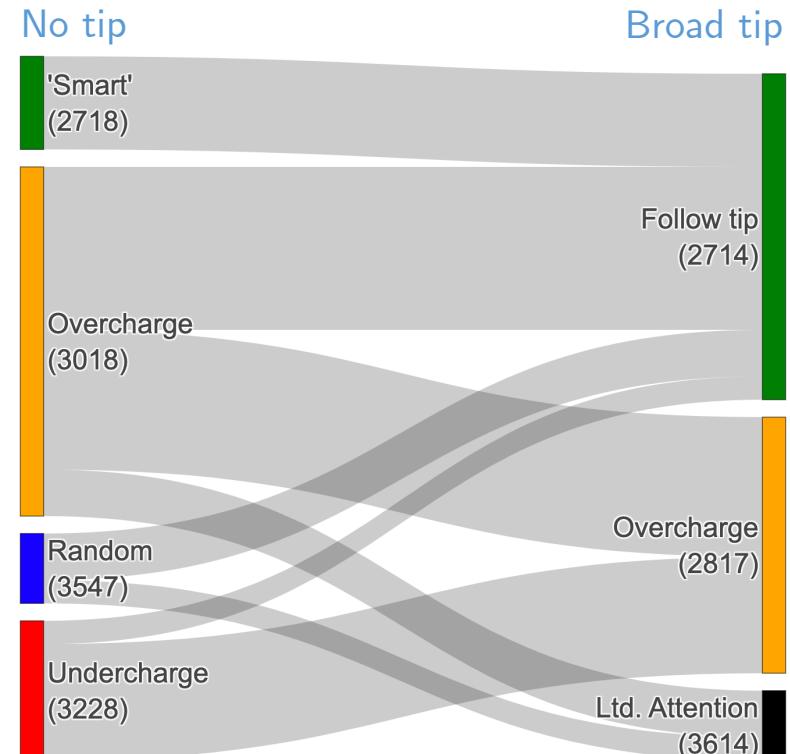
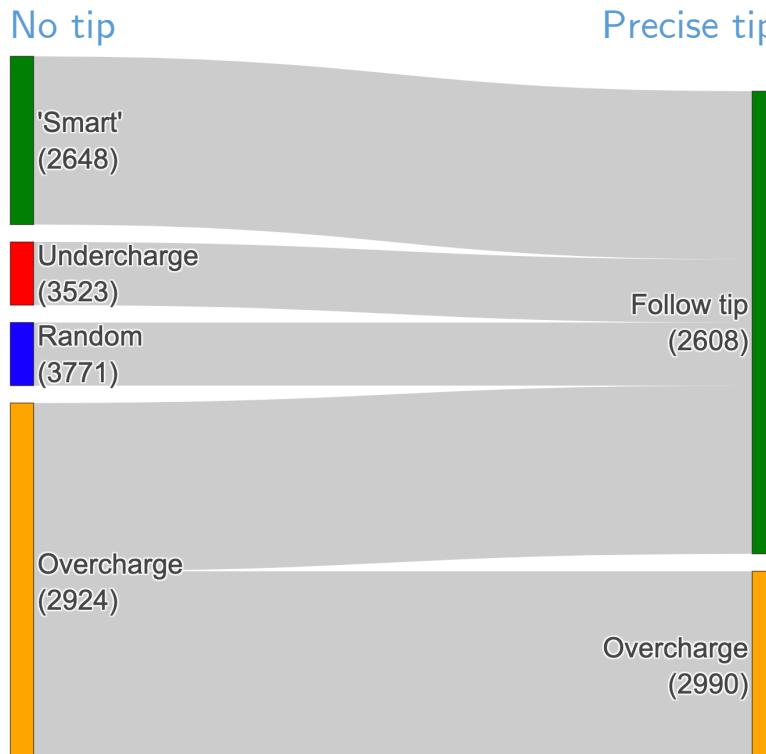
Study 2A: Results Predicting Response to Tip



Study 2A:

Results

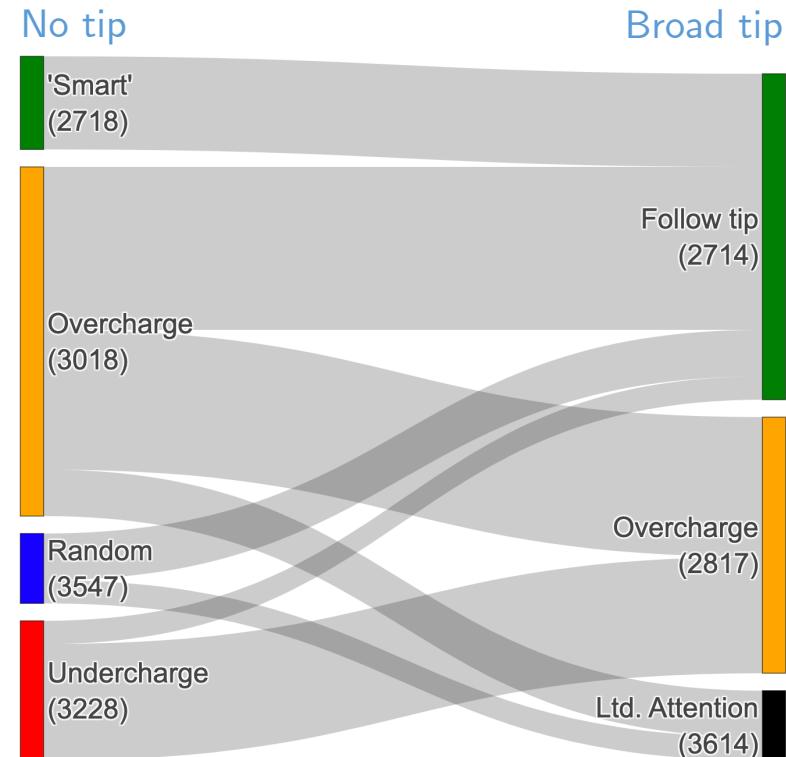
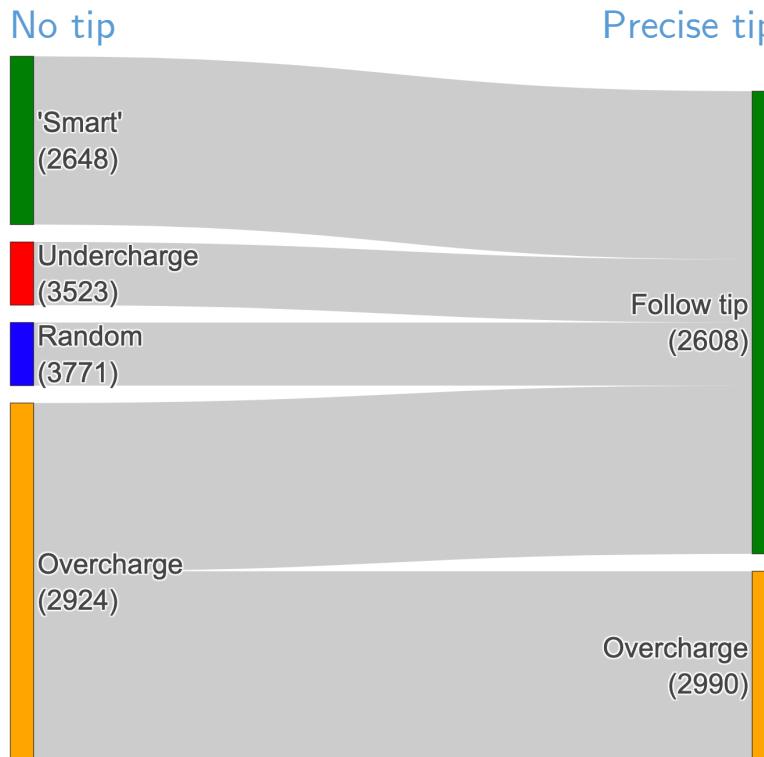
Predicting Response to Tip



Study 2A:

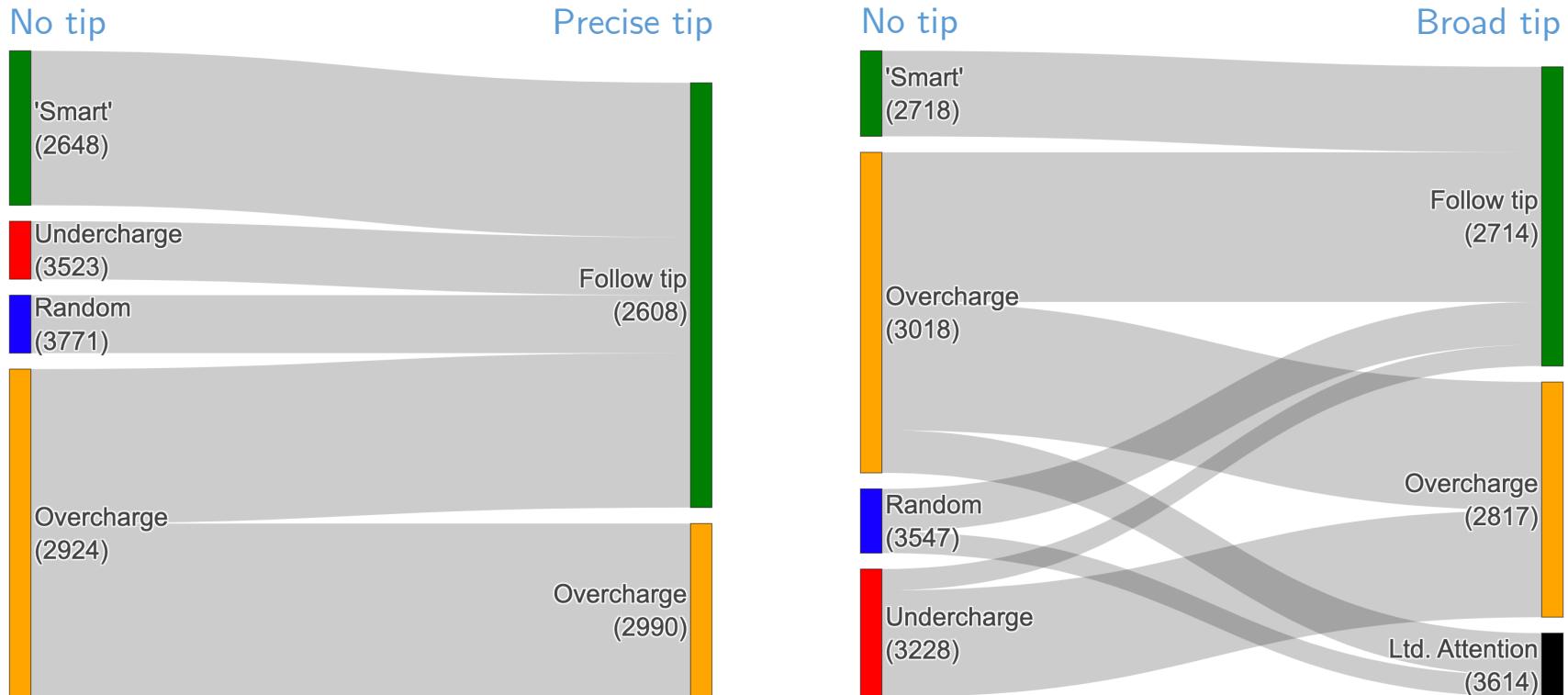
Results

Predicting Response to Tip



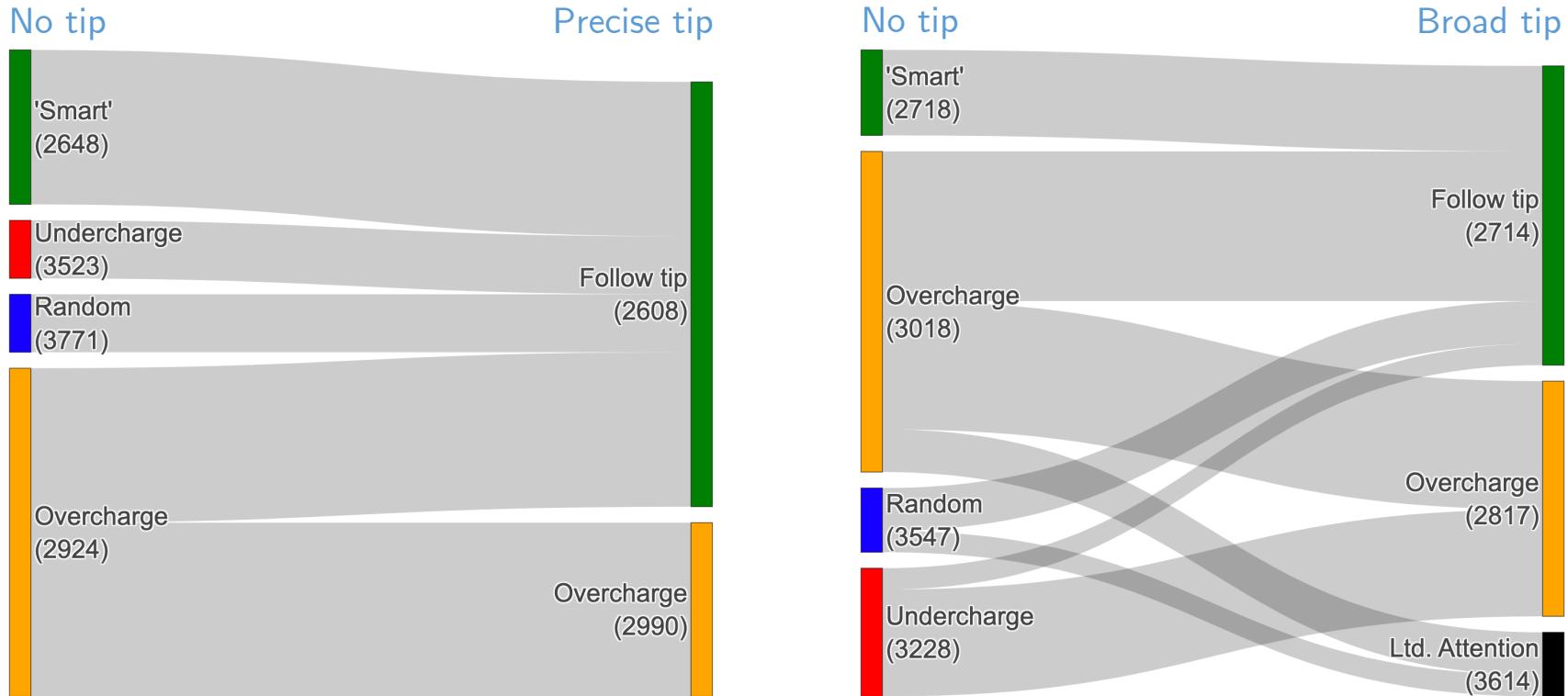
→ Advice followed exactly or more conservatively

Study 2A: Results Predicting Response to Tip



→ Advice followed exactly or more conservatively
→ Precise advice followed more

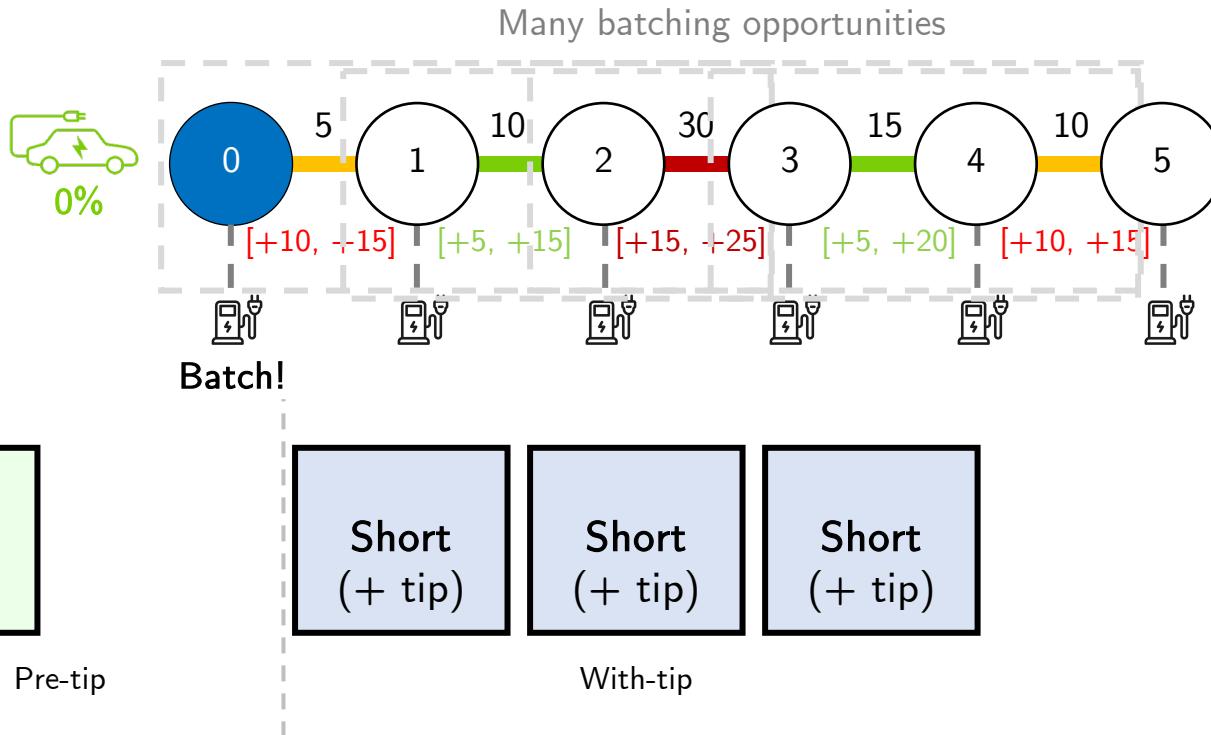
Study 2A: Results Predicting Response to Tip



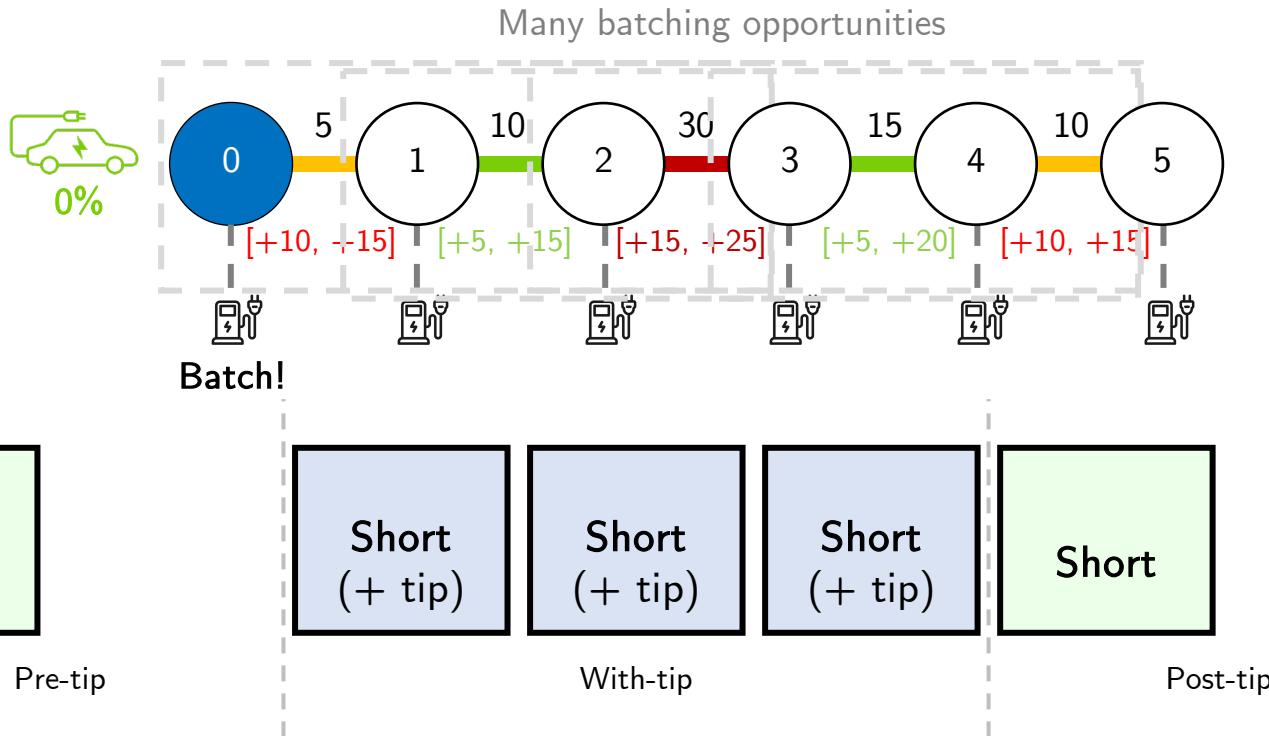
- Advice followed exactly or more conservatively
- Precise advice followed more
- “Smart” behavior is good indicator of “converting” imprecise tips

**But Did We Help Them
Improve Their Decision-Making?**

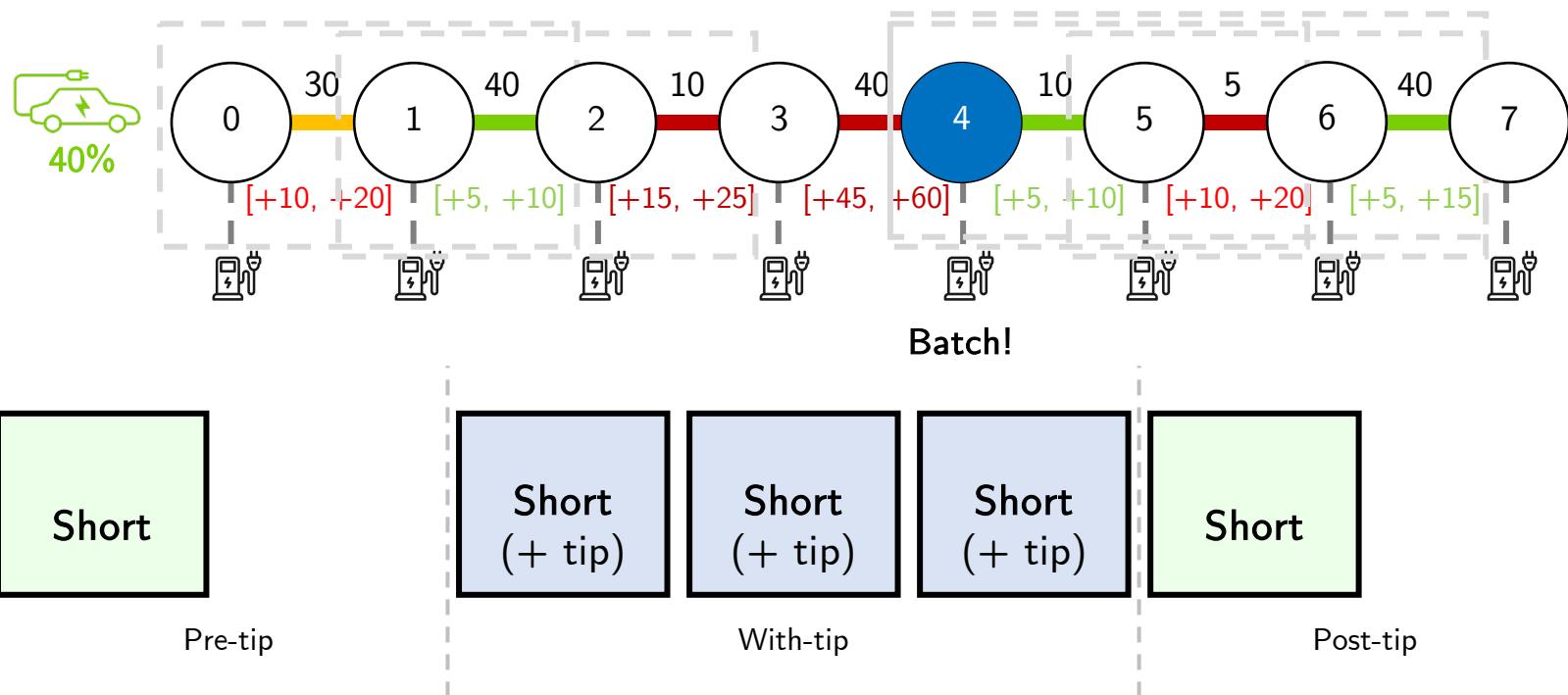
Study 2B: Design Short Map



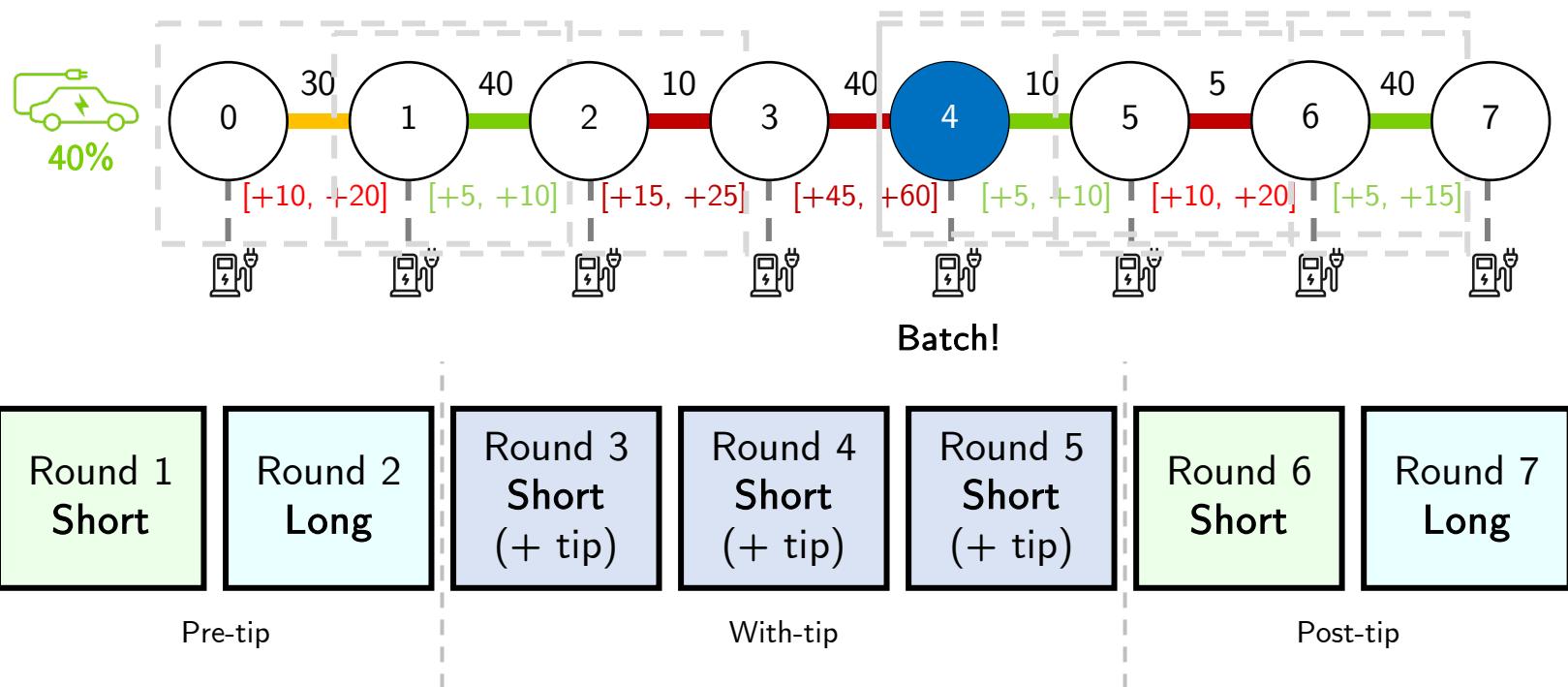
Study 2B: Design Short Map



Study 2B: Design + Long Map (New Environment)

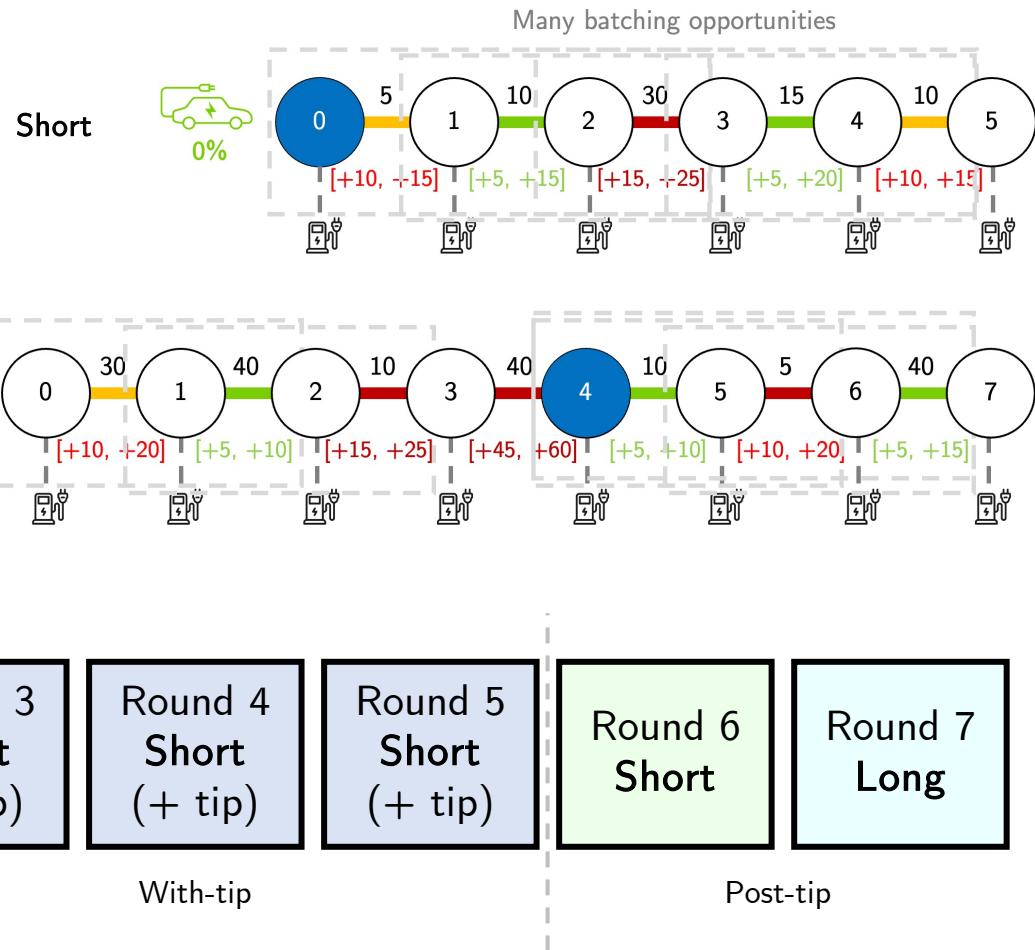


Study 2B: Design + Long Map (New Environment)



Study 2B:

Design



2 x 2

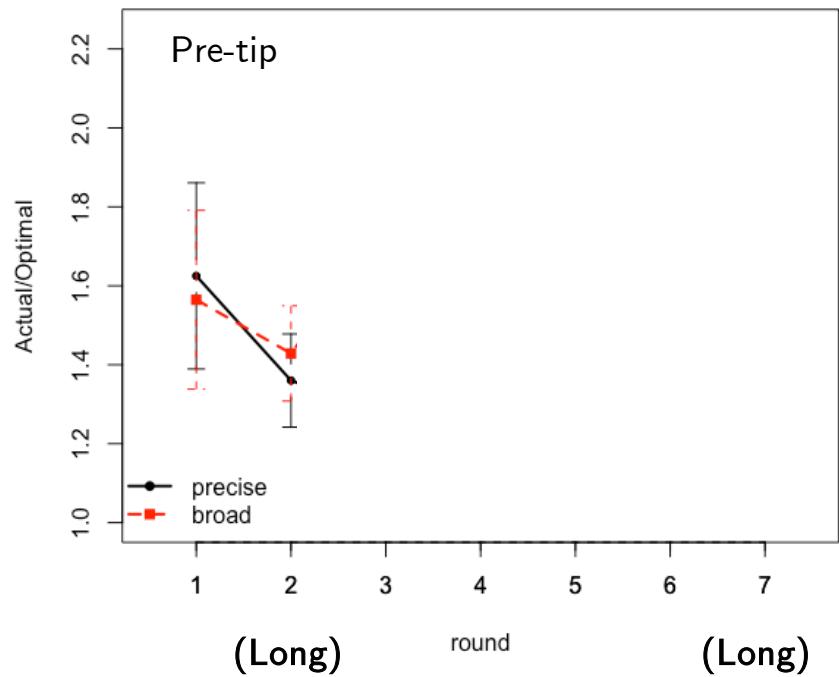
precise / broad
tip

centered / skewed
realized traffic

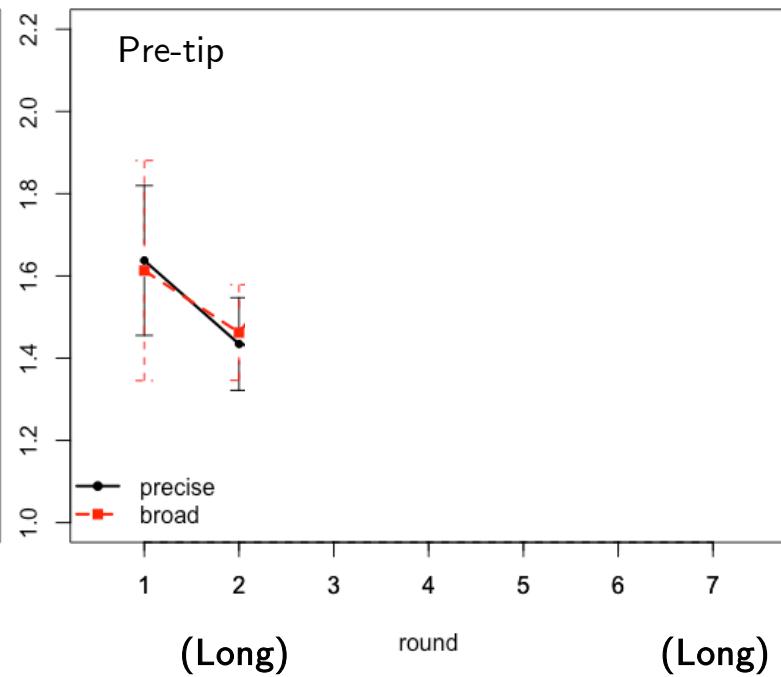
Study 2B:

Results

Normalized Performance by Tip Condition (Centered)

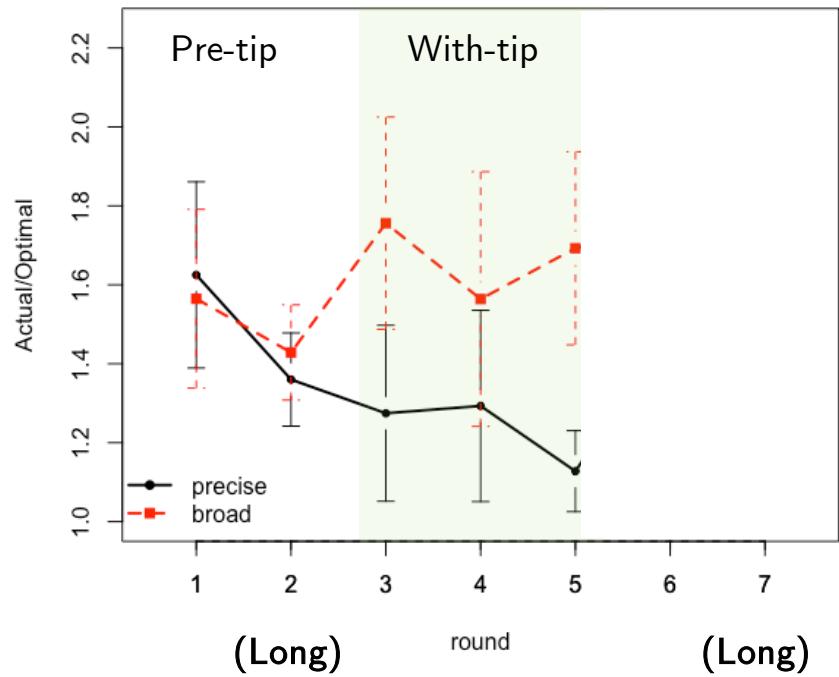


Normalized Performance by Tip Condition (Skewed)

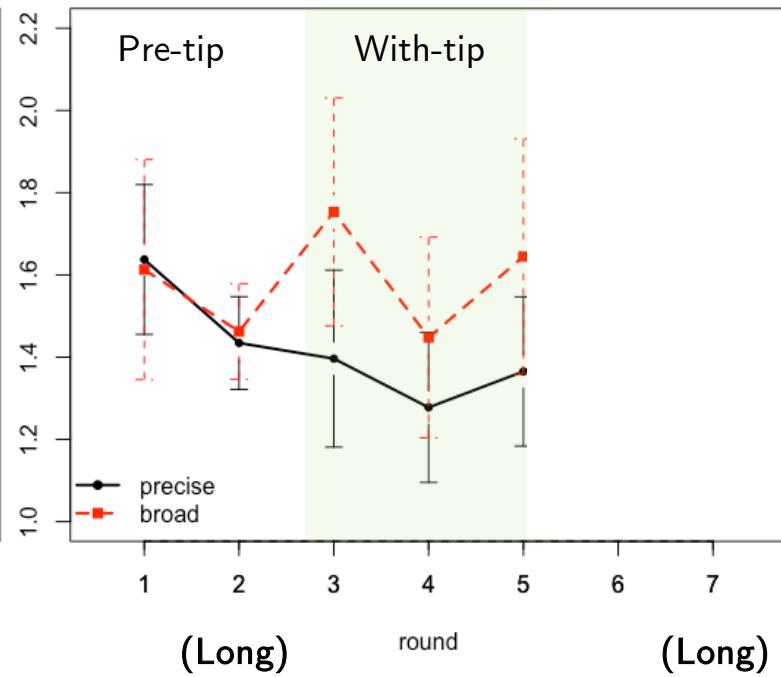


Study 2B: Results

Normalized Performance by Tip Condition (Centered)



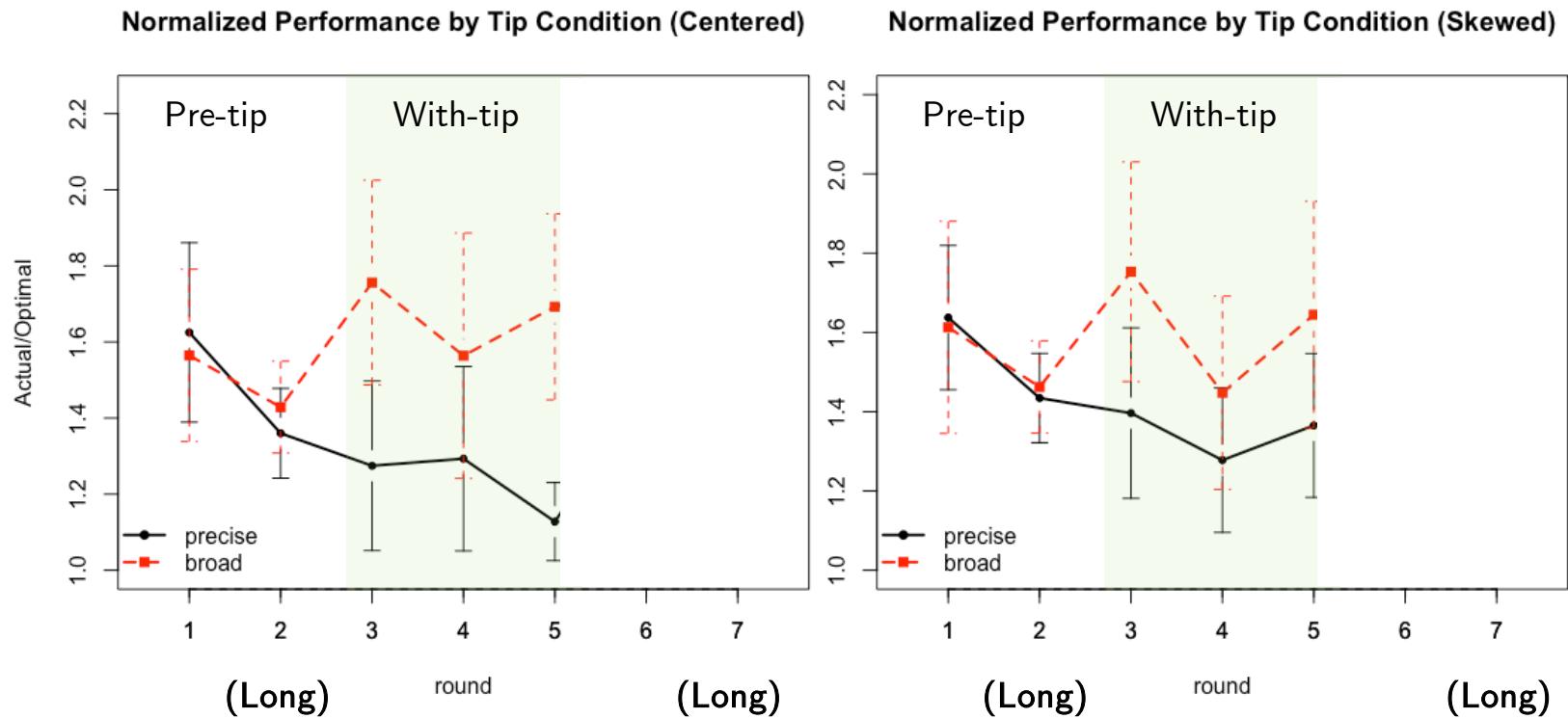
Normalized Performance by Tip Condition (Skewed)



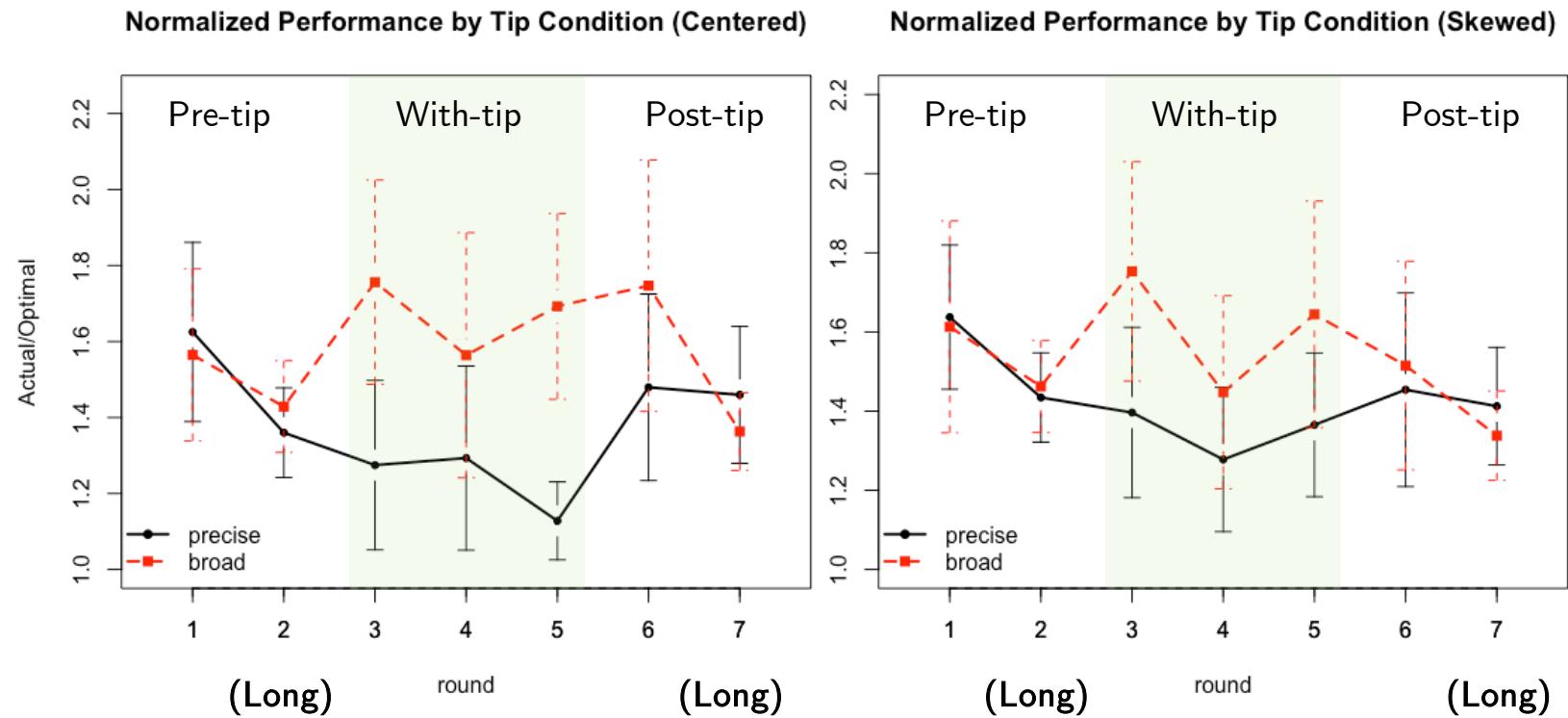
Study 2B:

Results

Precise Tip Worked, Again



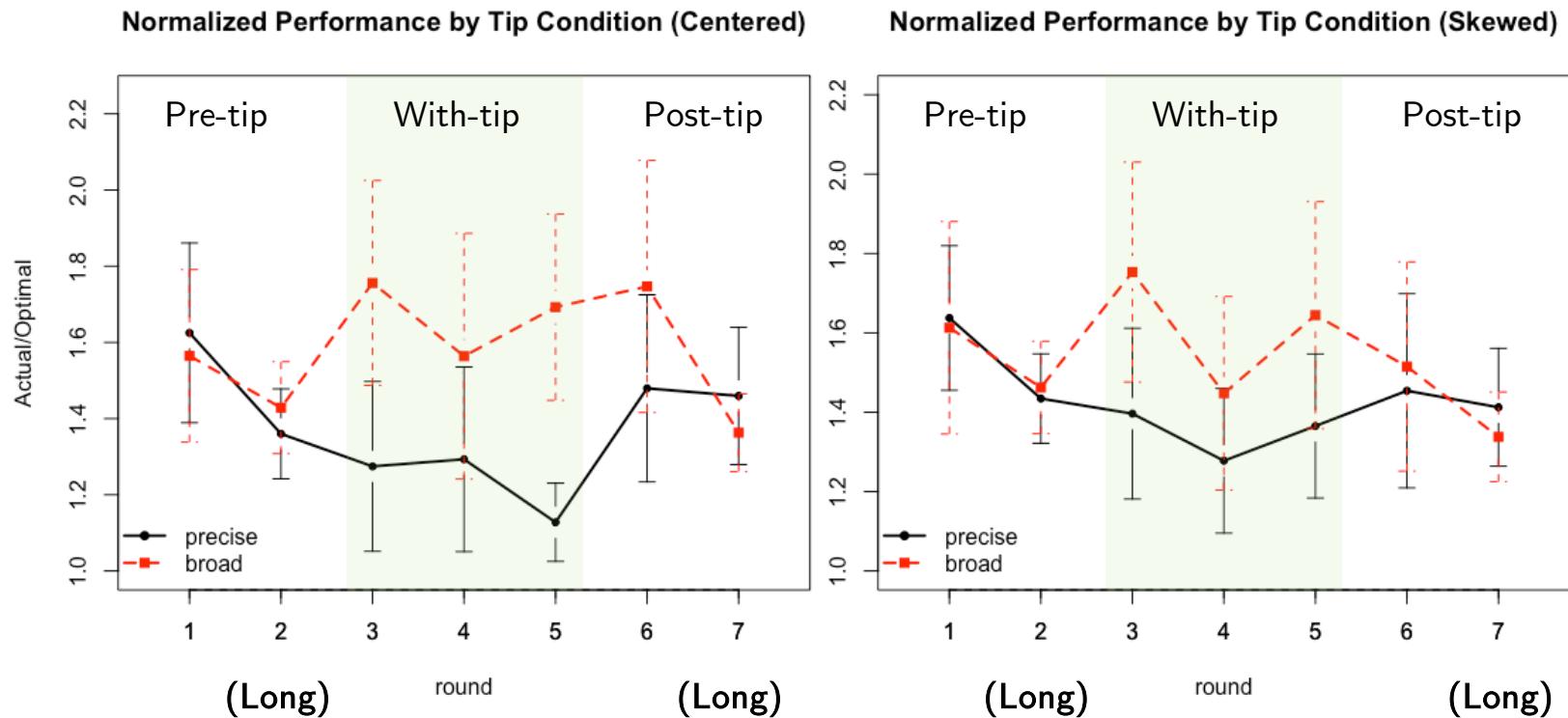
Study 2B: Results



Study 2B:

Results

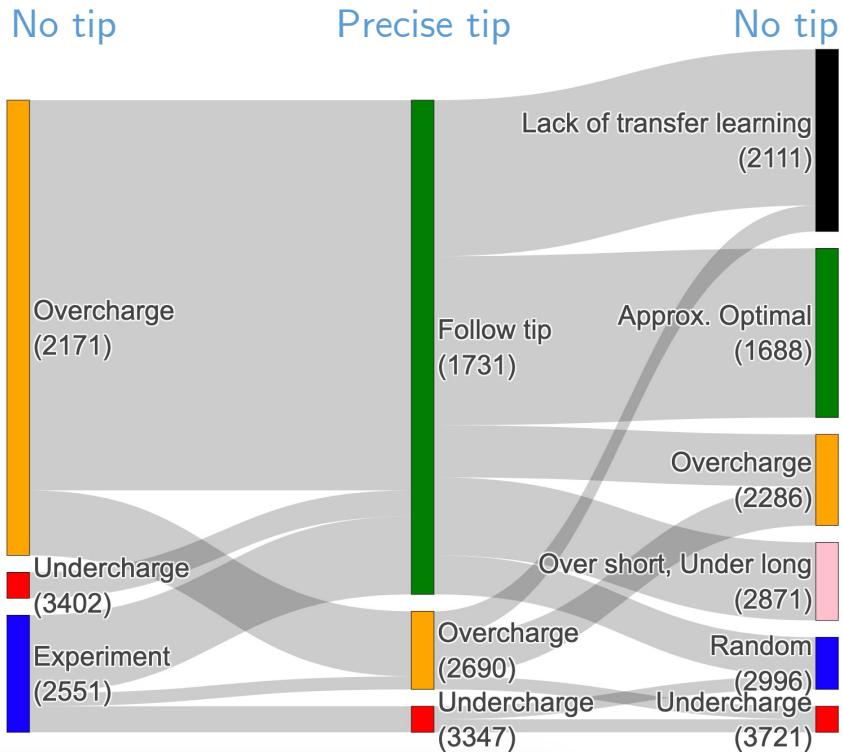
Broad Tip Seemed to Help with New Environment



Study 2B:

Results

Long-Term Learning from Tip



34% stay with
optimal strategy afterwards

Study 2B:

Results

Long-Term Learning from Tip

No tip

Precise tip

No tip

Overcharge
(2171)

Undercharge
(3402)
Experiment
(2551)

Follow tip
(1731)

Overcharge
(2690)
Undercharge
(3347)

Approx. Optimal
(1688)

Overcharge
(2286)

Over short, Under long
(2871)

Random
(2996)
Undercharge
(3721)

Lack of transfer learning
(2111)

No tip

Broad tip

No tip

Overcharge
(2118)

Experiment
(2525)

Undercharge
(3723)

Follow tip
(2054)

Overcharge
(2667)

Undercharge
(3657)

Approx. Optimal
(1761)

Overcharge
(2313)

Random
(2650)

Lack of transfer learning
(2164)

Over short, Under long
(2871)

Undercharge
(3222)

34% stay with
optimal strategy afterwards

56% stay with
optimal strategy afterwards

Summary

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



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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)

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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*



Summary

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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*



Feedback (+ tips) very welcome!

Results Learning Beyond Tips

Structure of Optimal Policy

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

Results Learning Beyond Tips

Structure of Optimal Policy

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

Results Learning Beyond Tips

Structure of Optimal Policy

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

Algorithm Baseline

The diagram illustrates the structure of an optimal policy for two roles: Sous-Chef and Server. The policy is organized into three columns: Chop, Cook, and Plate. The Sous-Chef row contains values 3, 2, 2, with a chef's hat icon above the 3. The Server row contains values 1, 2, 2, with a chef's hat icon above the 1. The values 3 and 1 are highlighted with a light blue background. Arrows point from the labels "Algorithm" and "Baseline" at the bottom to the sous-chef's "Chop" and server's "Cook" values, respectively.

Results Learning Beyond Tips

Sous-Chef
chops 3 times



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

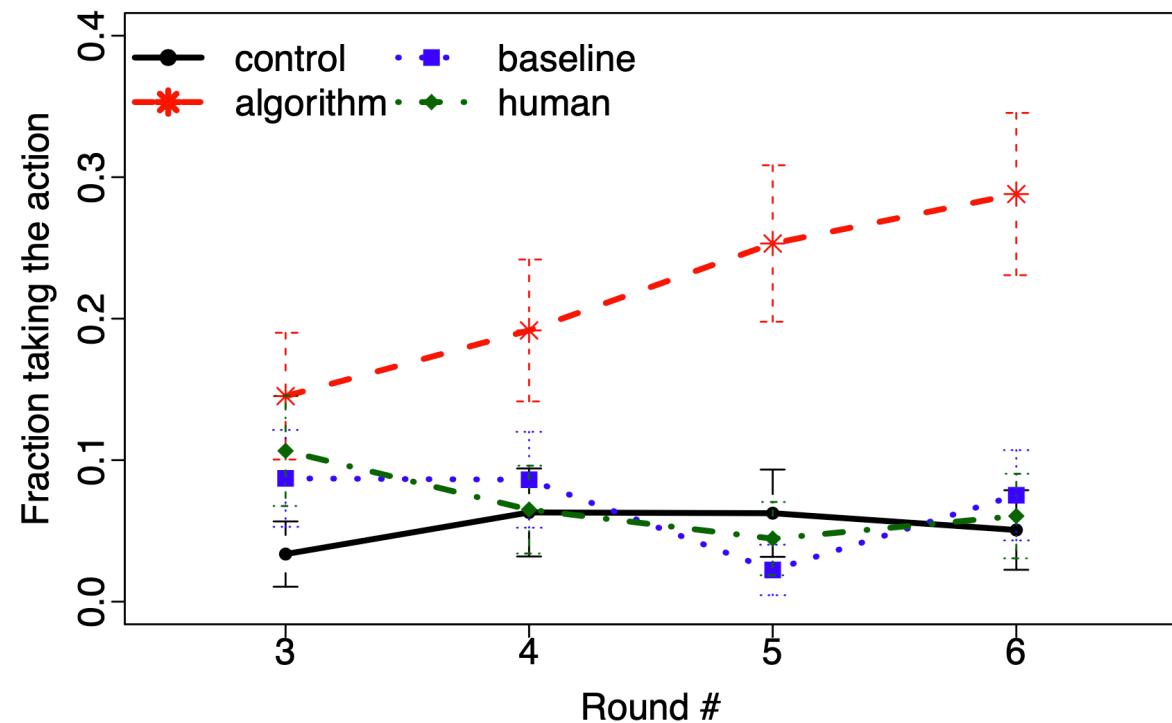
Results Learning Beyond Tips

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

Sous-Chef
chops 3 times

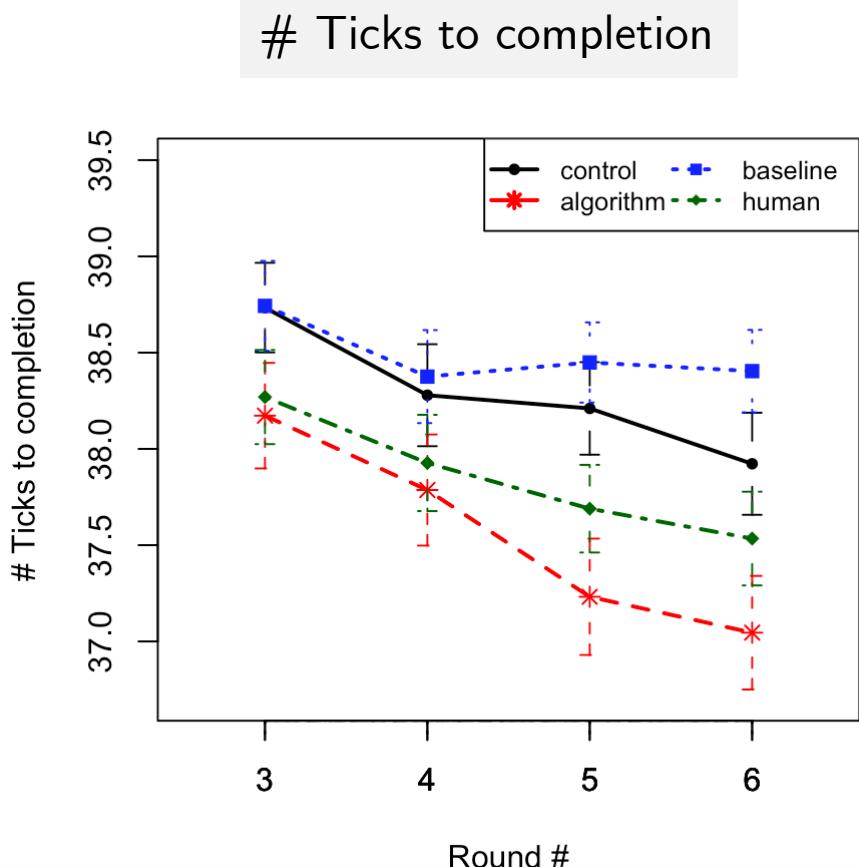


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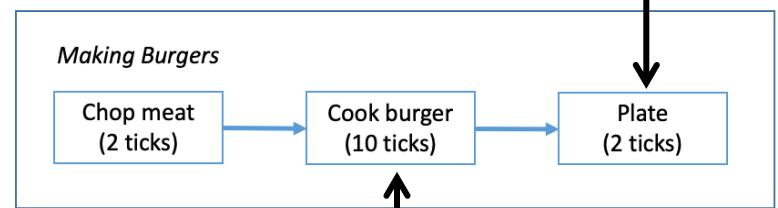


Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Results Good Tip = Consequential



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

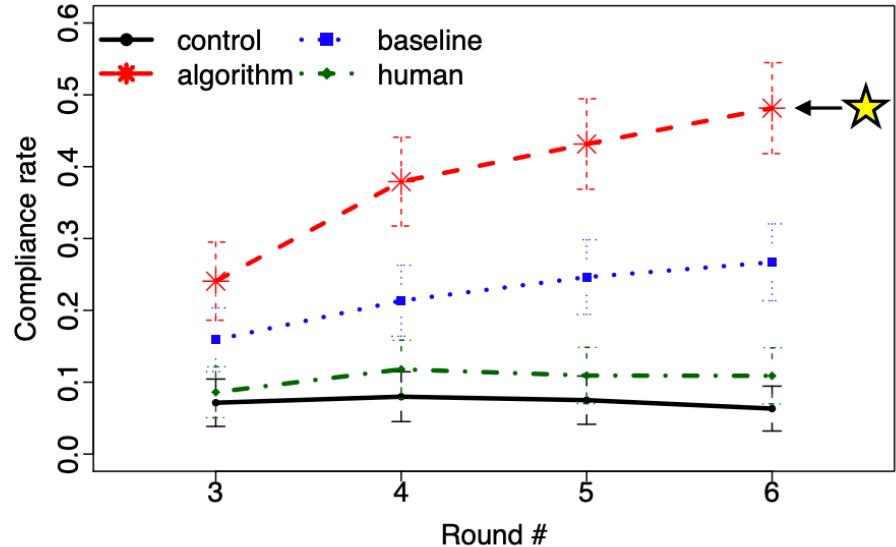
	Phase I: Normal	Phase II: Normal	Phase I: Disrupted	Phase II: Disrupted
Total	183	1,317	172	1,011
Mean age [range]	34.6 [18, 76]	33.3 [18, 74]	34 [19, 76]	34.9 [16, 84]
Female	57.38%	51.03%	61.63%	60.14%
≥ 2-year degree	73.22%	67.73%	77.91%	70.43%
Median duration	18.82 minutes	20.50 min	27.80 min	26.80 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%		

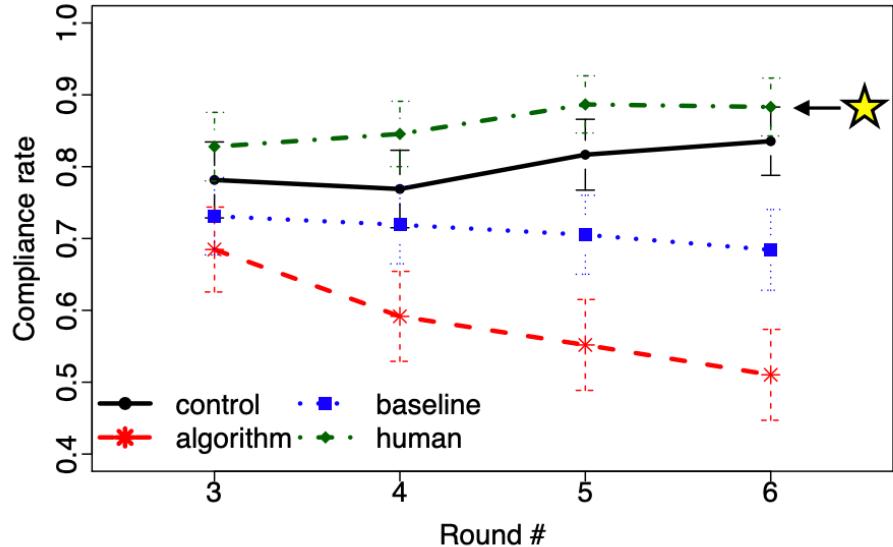
Table 7: Participants’ coded feedback on the provided tips (normal configuration).

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

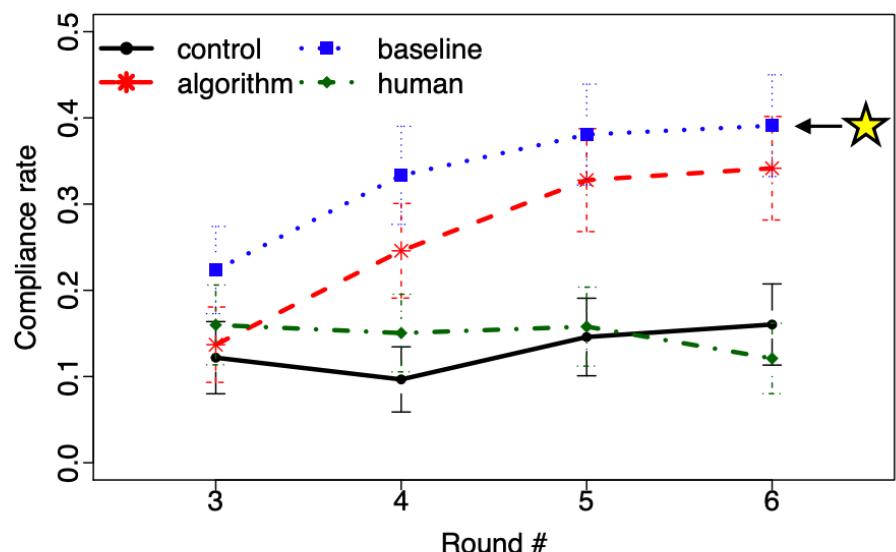
Table 8: Participants’ coded feedback on the provided tips (disrupted configuration).



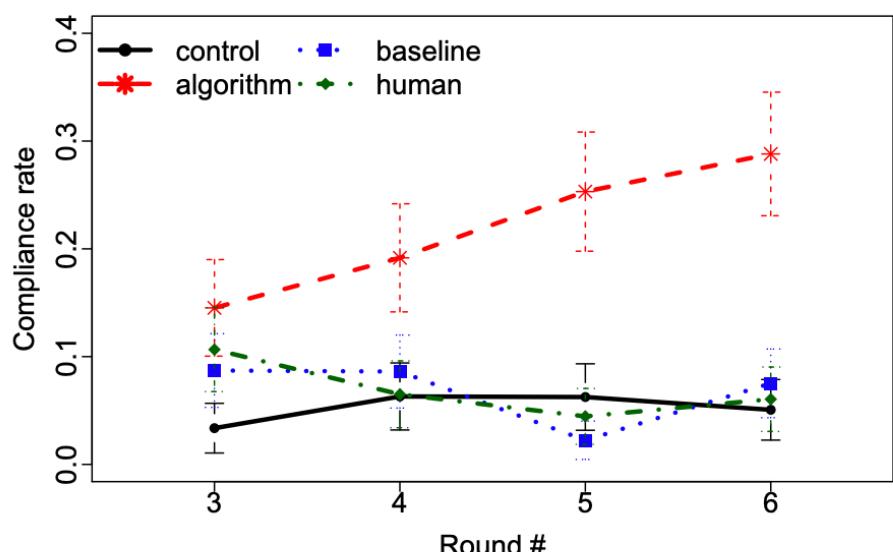
(a) Algorithm Tip: “Server cooks twice”



(b) Human Tip: “Server cooks once”

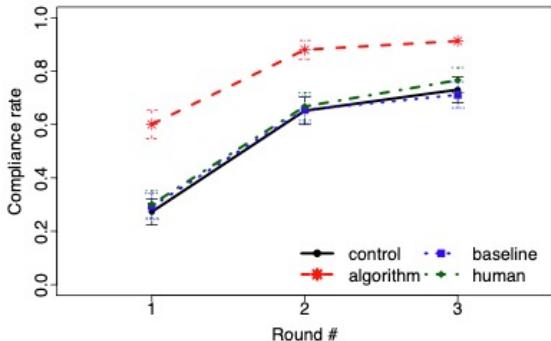


(c) Baseline Tip: “Sous-chef plates twice”

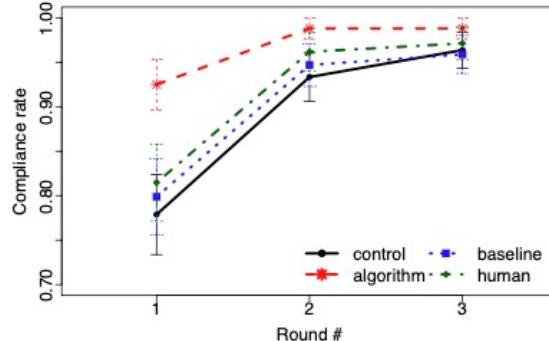


(d) Unshown Tip: “Server chops once”

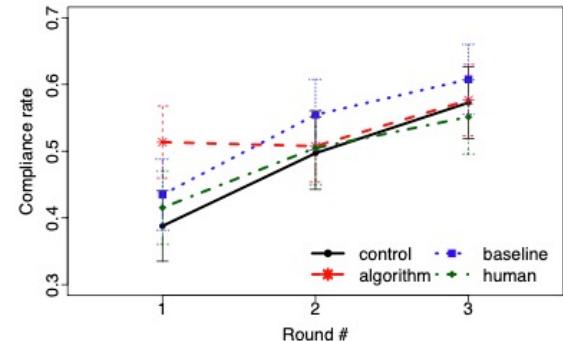
Learning Beyond Tips



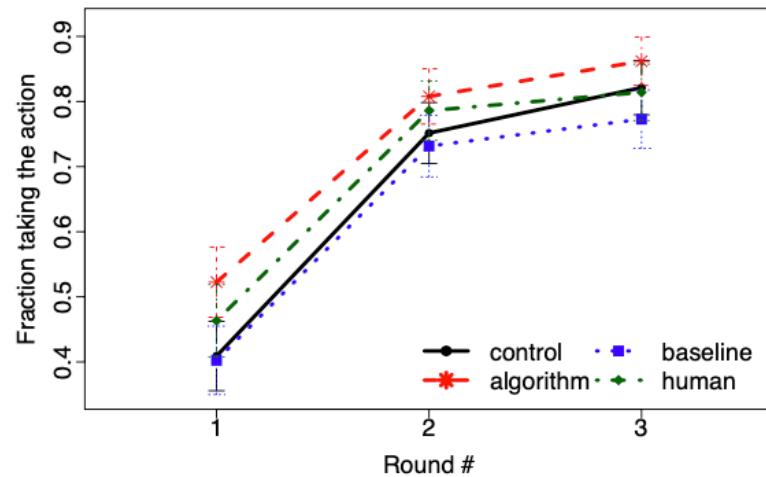
(a) Algorithm: “Chef shouldn’t plate”



(b) Human: “Leave some idle”



(c) Baseline: “Chef chops once”



(a) Fully-staffed: “Server shouldn’t cook”

Next Tick	Current Tick: 0/50	Orders Completed: 0
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Tip: Never assign plating to the Chef.

Orders

burger (0/3) chop meat (2 ticks)	burger (0/3) chop meat (2 ticks)	burger (0/3) chop meat (2 ticks)	burger
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Workers

chef	sous-chef	server

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

Next Tick	Current Tick: 1/50	Orders Completed: 0
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Tip: Never assign plating to the Chef.

Orders

burger (0/3)	burger (0/3)	burger (0/3)	burger
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Workers

chef	sous-chef	server

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