

Improving Human Decision-Making with Machine Learning

Park Sinchaisri
Berkeley Haas



with Hamsa Bastani (Wharton)
& Osbert Bastani (Penn)



Learning is Costly

2+ years

to be fully productive

\$1,286/worker

training expenses

- Training Magazine 2019

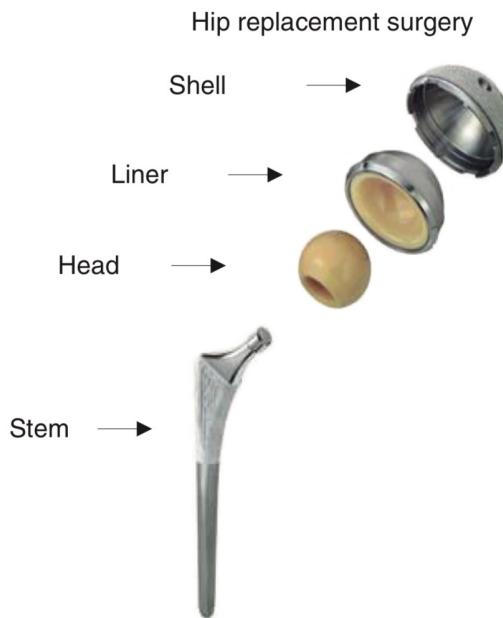
Learning is Costly

2+ years
to be fully productive

\$1,286/worker

training expenses

- Training Magazine 2019



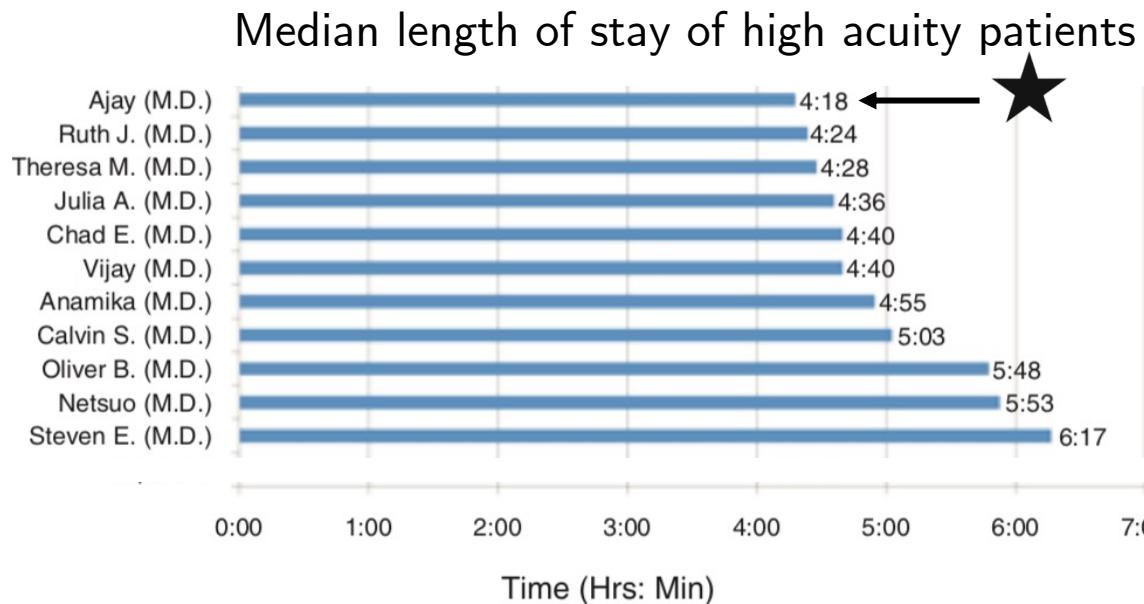
New device = **+32.4%**
surgery duration

- Ramdas et al. 2018

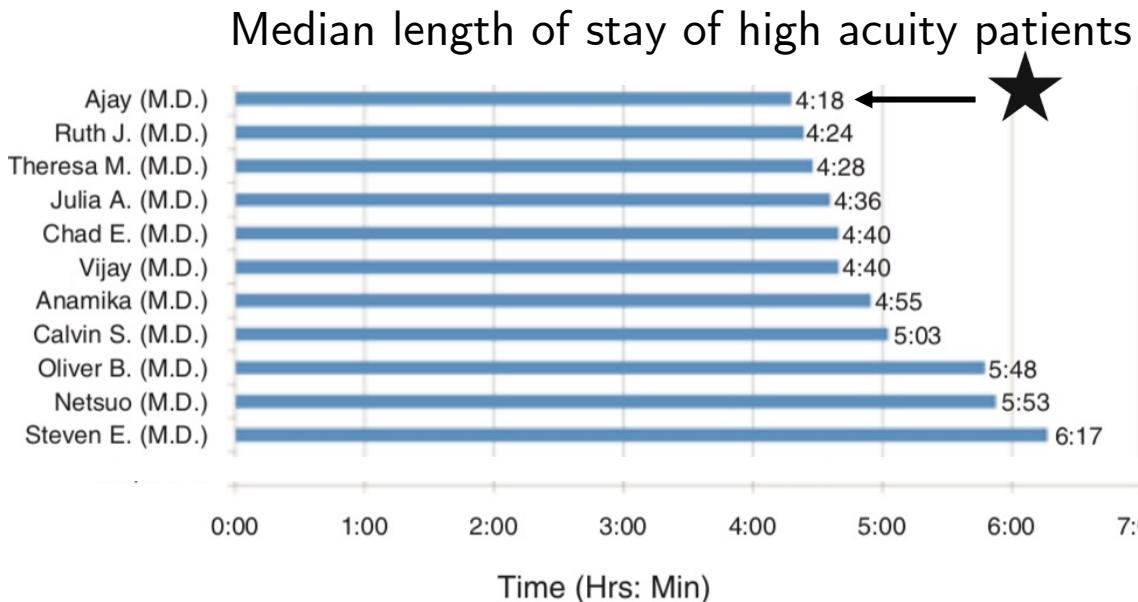
Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019,
Bavafa & Jonasson 2020, Bloom et al 2020, ...

Learning from Experts

Learning from Experts



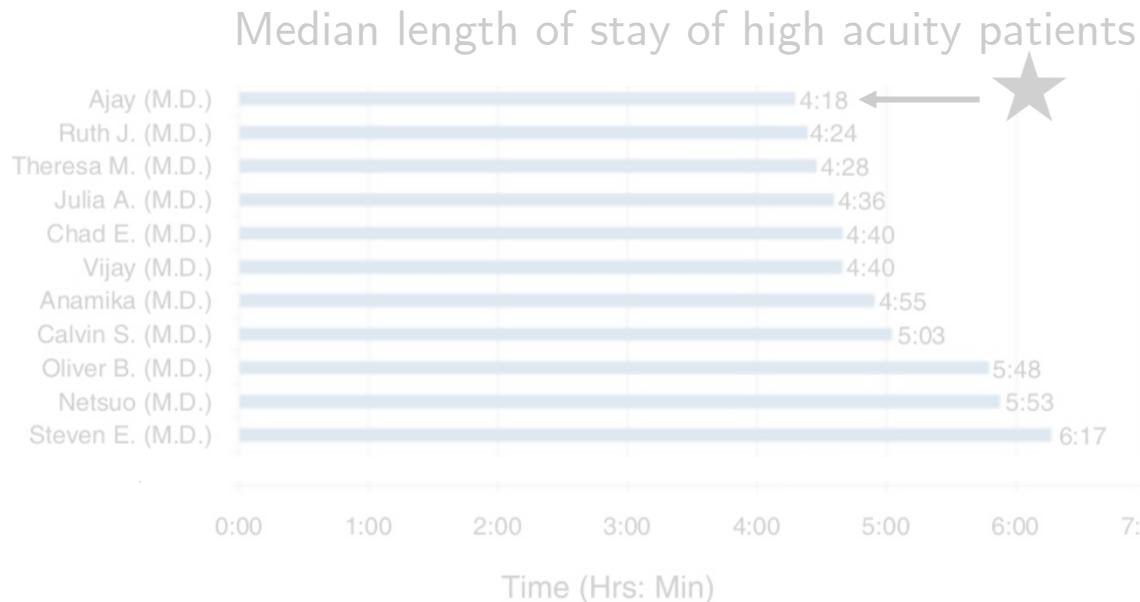
Learning from Experts



+10.9%
productivity
- Song et al. 2018

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

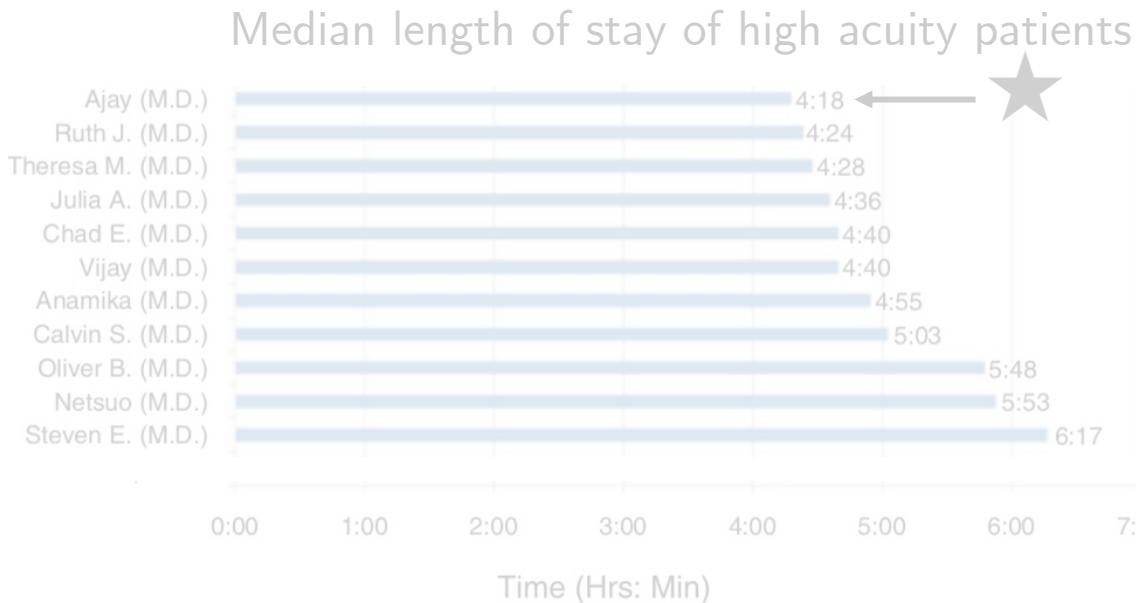
Learning from Experts



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

Uber Drivers



Trace Data is Everywhere

Physicians

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

Uber Drivers



Trace data



Tips

Trace Data is Everywhere

Physicians

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

Uber Drivers



Trace data

Tips

Noisy, high-volume data
hard to extract insights

Trace Data is Everywhere

Physicians

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

Uber Drivers



Trace data



Tips

Noisy, high-volume data
hard to extract insights

Key Q: can insights from ML
improve human decision-making?

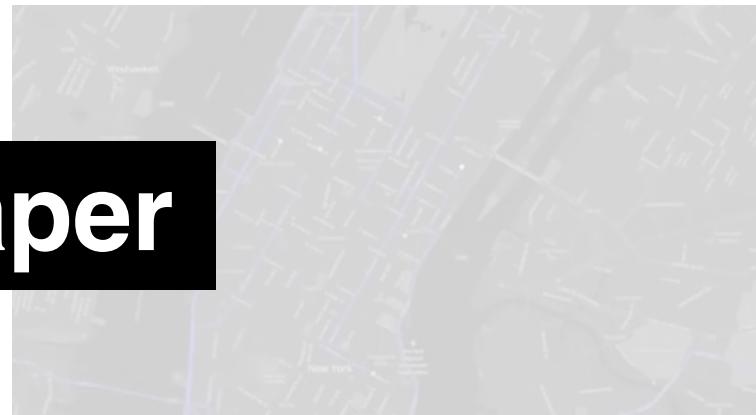
Trace Data is Everywhere

Physicians

• ROACH,TRISTIN	Fibrinogen, INR, PT, PTT AMD_996304_76
• ROACH,TRISTIN	Lipitor 80 mg
• LEON,ERIN	Geriatric Wellness Visit
• BECK,ALIVIA	Zocor 20 mg
NORTON,BETHANY	Norvasc 10 mg
MONTGOMERY,BLAINE	Glucophage 850 mg
KLECK,MICHAEL	Office Visit - Abbreviated
MCARDLE,HELEN	Office Visit - Mobile

	MILLER,ALEX,MD status: Unreviewed	05•19•17
	MILLER,ALEX,MD status: Unreviewed	05•18•17
	JONES,CAMERON,MD status: Unreviewed	05•16•17
	JONES,CAMERON,MD status: Reviewed	05•18•17
	JONES,CAMERON,MD reviewed by: SUSAN status: Reviewed	05•12•17
	JONES,CAMERON,MD status: Unreviewed	05•12•17

Uber Drivers



Our Paper

Extract
best practices

Mine
simple tips

Tips

Trace data

Machine
Learning



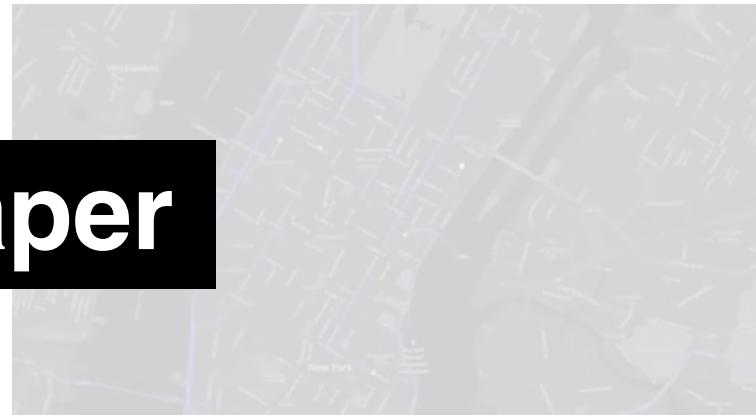
Trace Data is Everywhere

Physicians

• ROACH,TRISTIN	Fibrinogen, INR, PT, PTT AMD_996304_76
• ROACH,TRISTIN	Lipitor 80 mg
• LEON,ERIN	Geriatric Wellness Visit
• BECK,ALIVIA	Zocor 20 mg
NORTON,BETHANY	Norvasc 10 mg
MONTGOMERY,BLAINE	Glucophage 850 mg
KLECK,MICHAEL	Office Visit - Abbreviated
MCARDLE,HELEN	Office Visit - Mobile

	MILLER,ALEX,MD status: Unreviewed	05-19-17
	MILLER,ALEX,MD status: Unreviewed	05-18-17
	JONES,CAMERON,MD status: Unreviewed	05-16-17
	JONES,CAMERON,MD status: Reviewed	05-18-17
	JONES,CAMERON,MD status: Reviewed	05-12-17
	JONES,CAMERON,MD status: Unreviewed	05-12-17

Uber Drivers



Our Paper

Trace data

Extract
best practices

Machine
Learning

Mine
simple tips

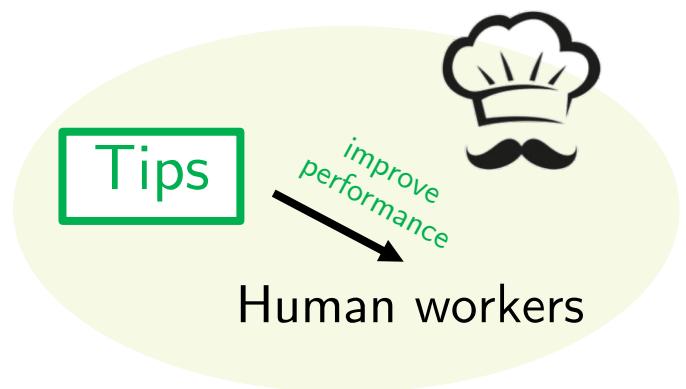
Tips



improve
performance

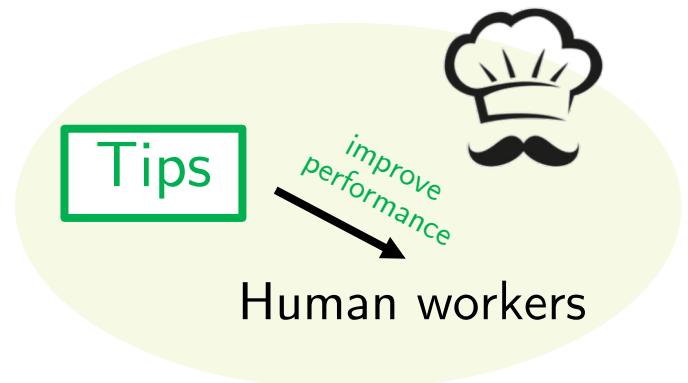
Human workers

Potential Issues



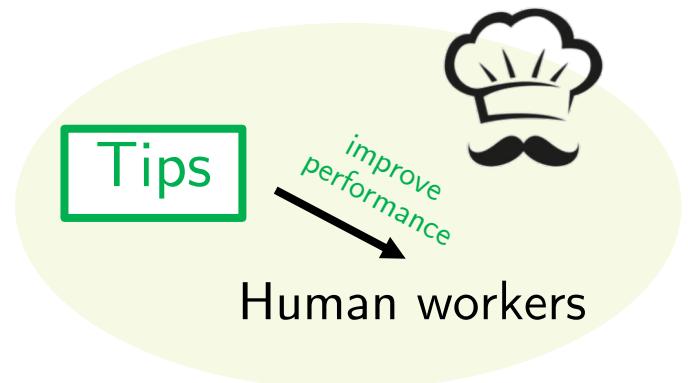
Potential Issues

- Compliance to tips, “algorithm aversion”
(e.g., Dawes et al 1989, Dietvorst et al 2015)



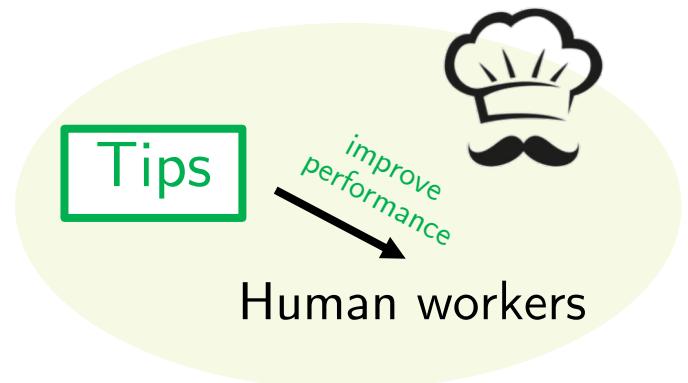
Potential Issues

- Compliance to tips, “algorithm aversion”
(e.g., Dawes et al 1989, Dietvorst et al 2015)
- Interpretability



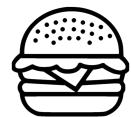
Potential Issues

- Compliance to tips, “algorithm aversion”
(e.g., Dawes et al 1989, Dietvorst et al 2015)
- Interpretability
- Learning curve

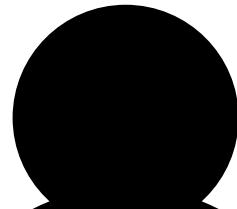


Queueing Game

Burger Queen



x 4 within 50 ticks



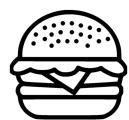
Participant

Pre-registered at

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

Queueing Game

Burger Queen



x 4 within 50 ticks

Making a Burger

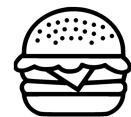
Chop meat
(2 ticks)

Cook burger
(10 ticks)

Plate
(2 ticks)

Queueing Game

Burger Queen



x 4 within 50 ticks

Chef



Sous-Chef



Server



Participant

Queueing Game

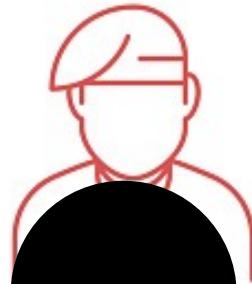
Burger Queen

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

Chef



Sous-Chef



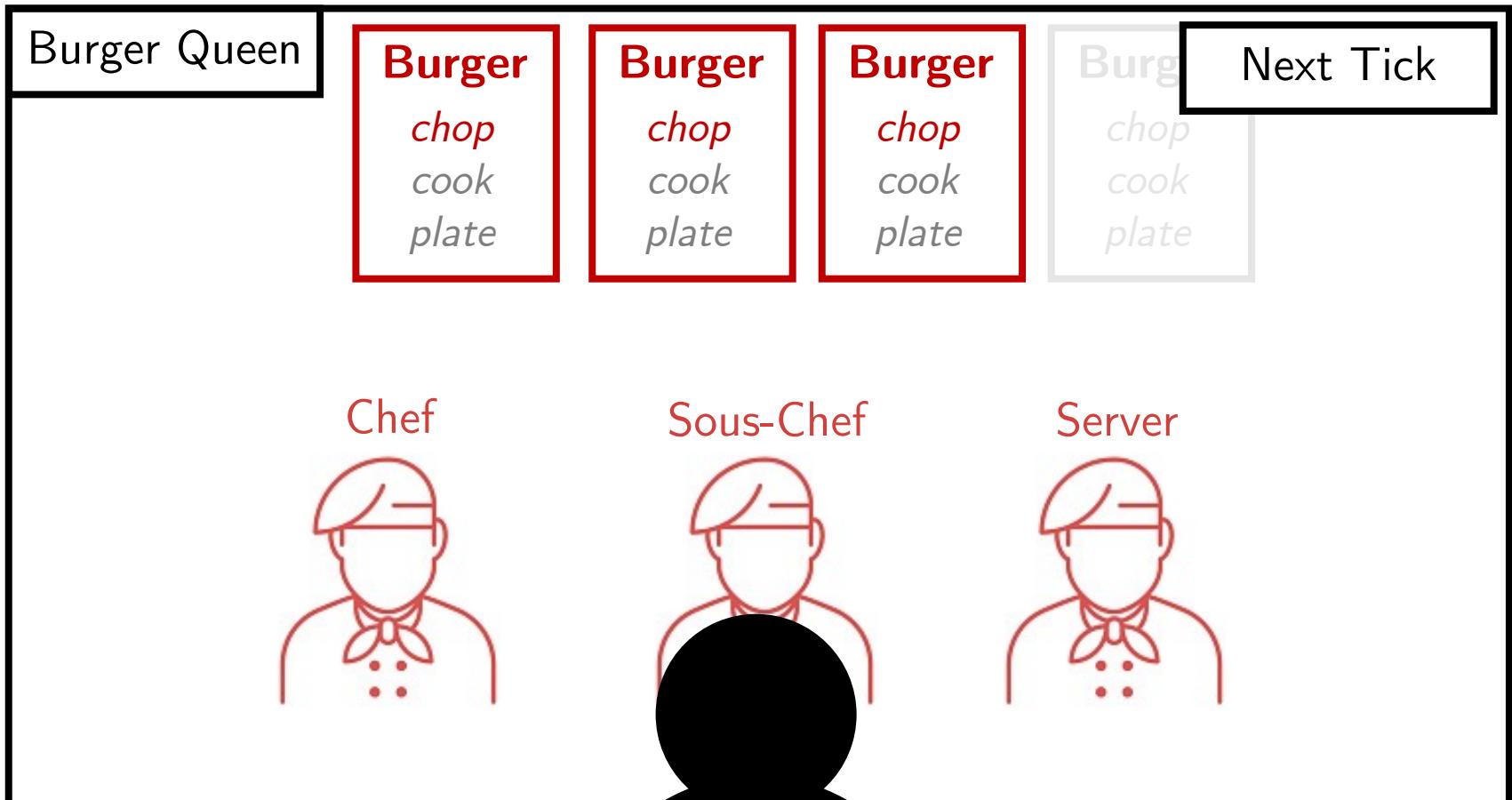
Server



Participant

Queueing Game

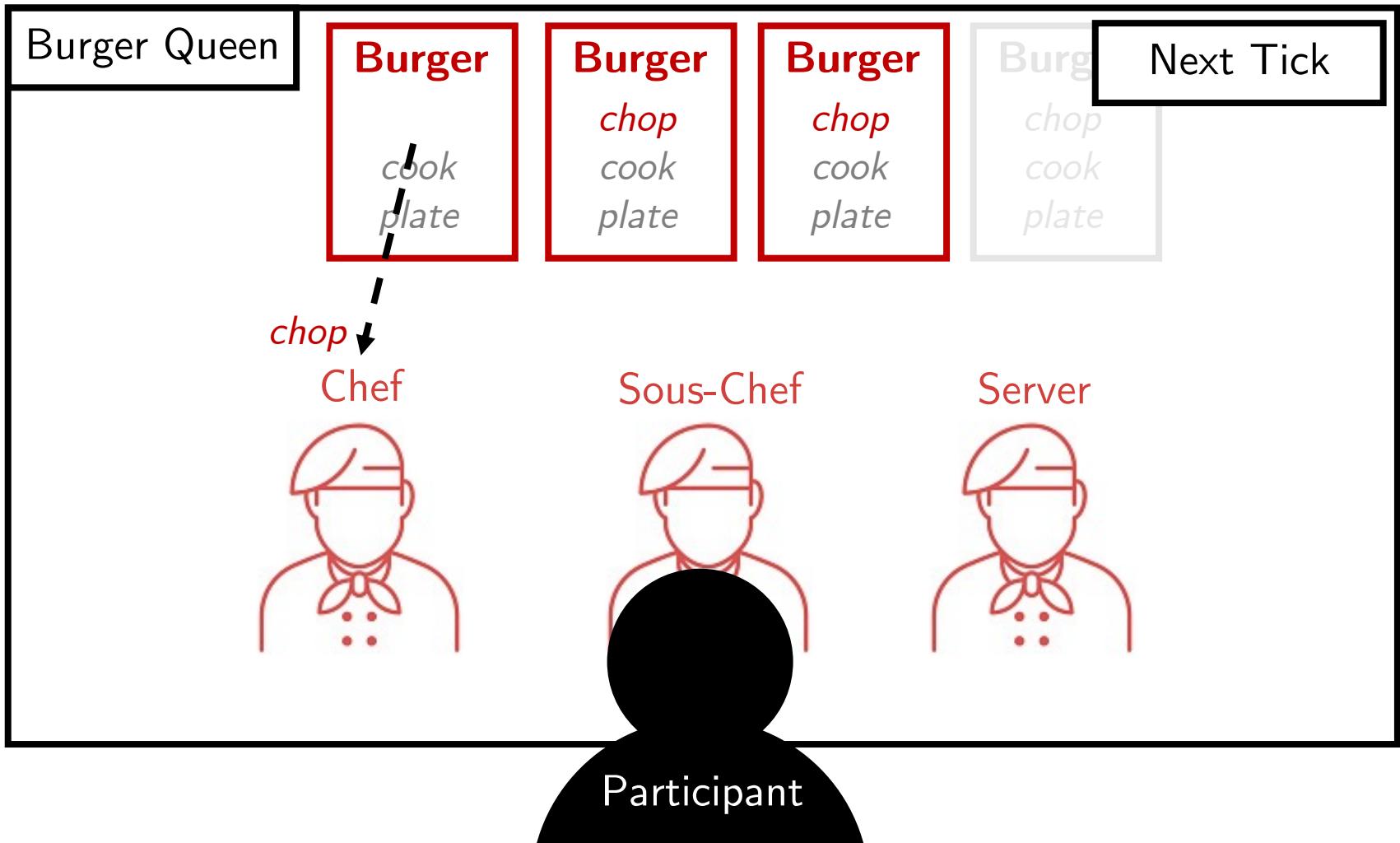
Reward: 0
Tick #1/50



Participant

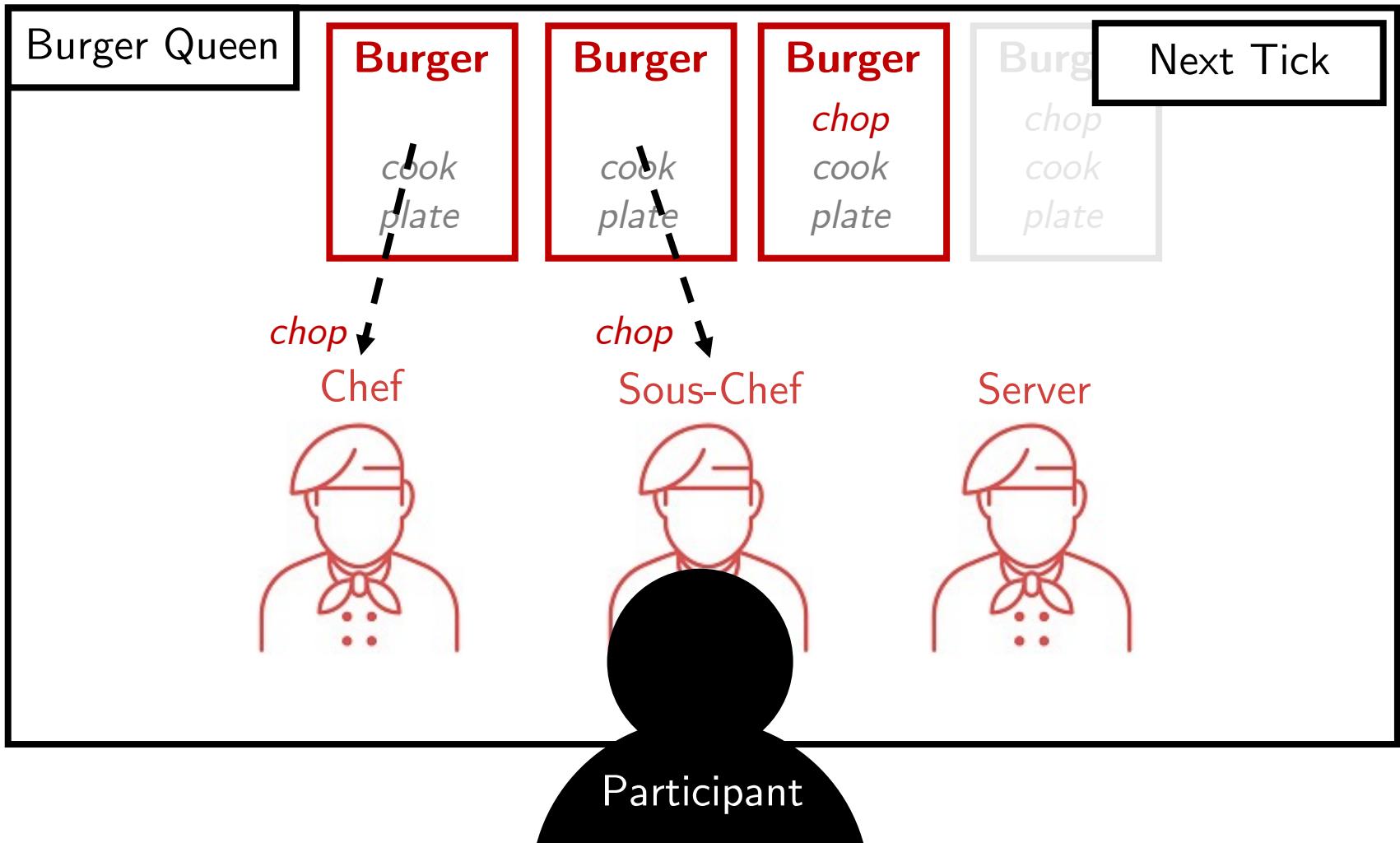
Queueing Game

Reward: 0
Tick #1/50



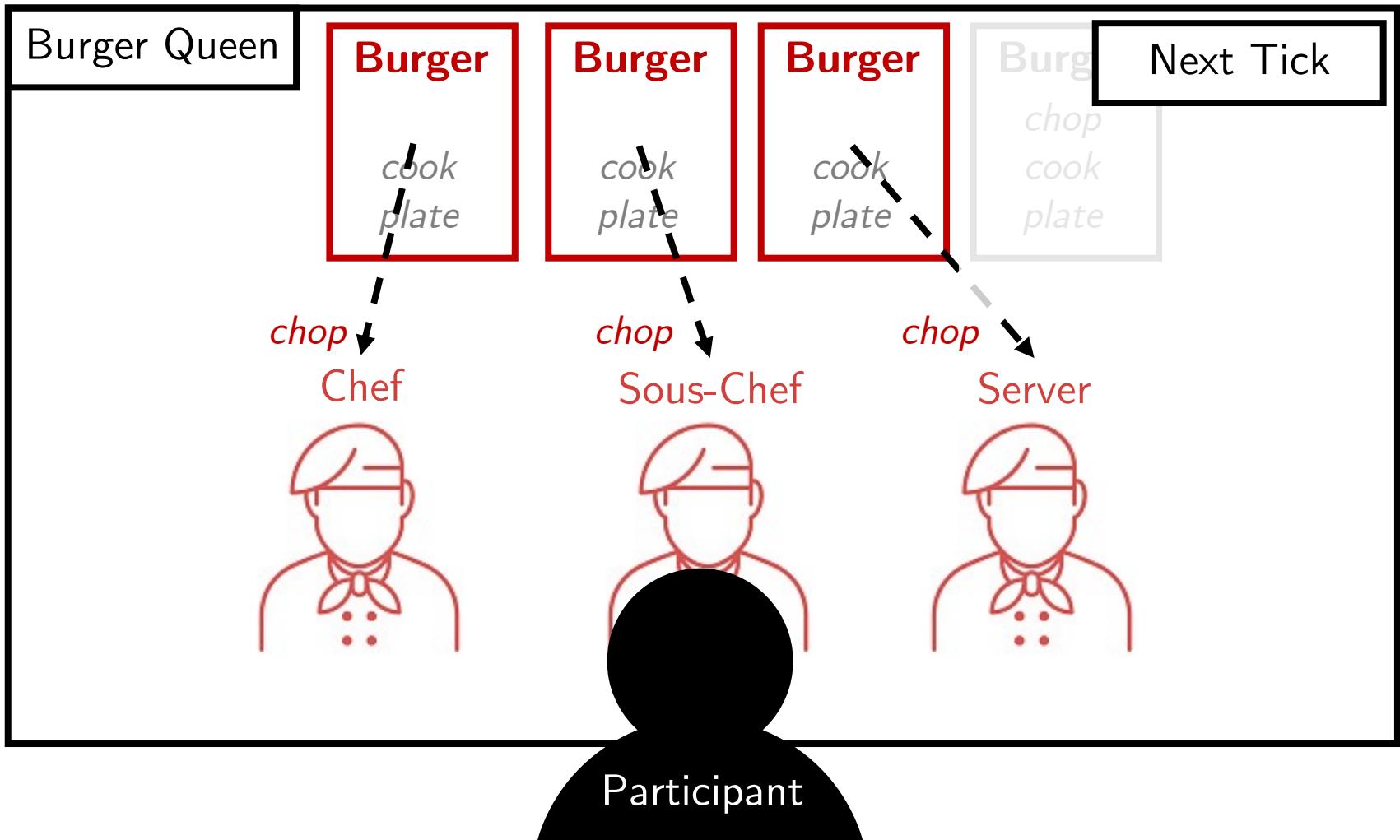
Queueing Game

Reward: 0
Tick #1/50



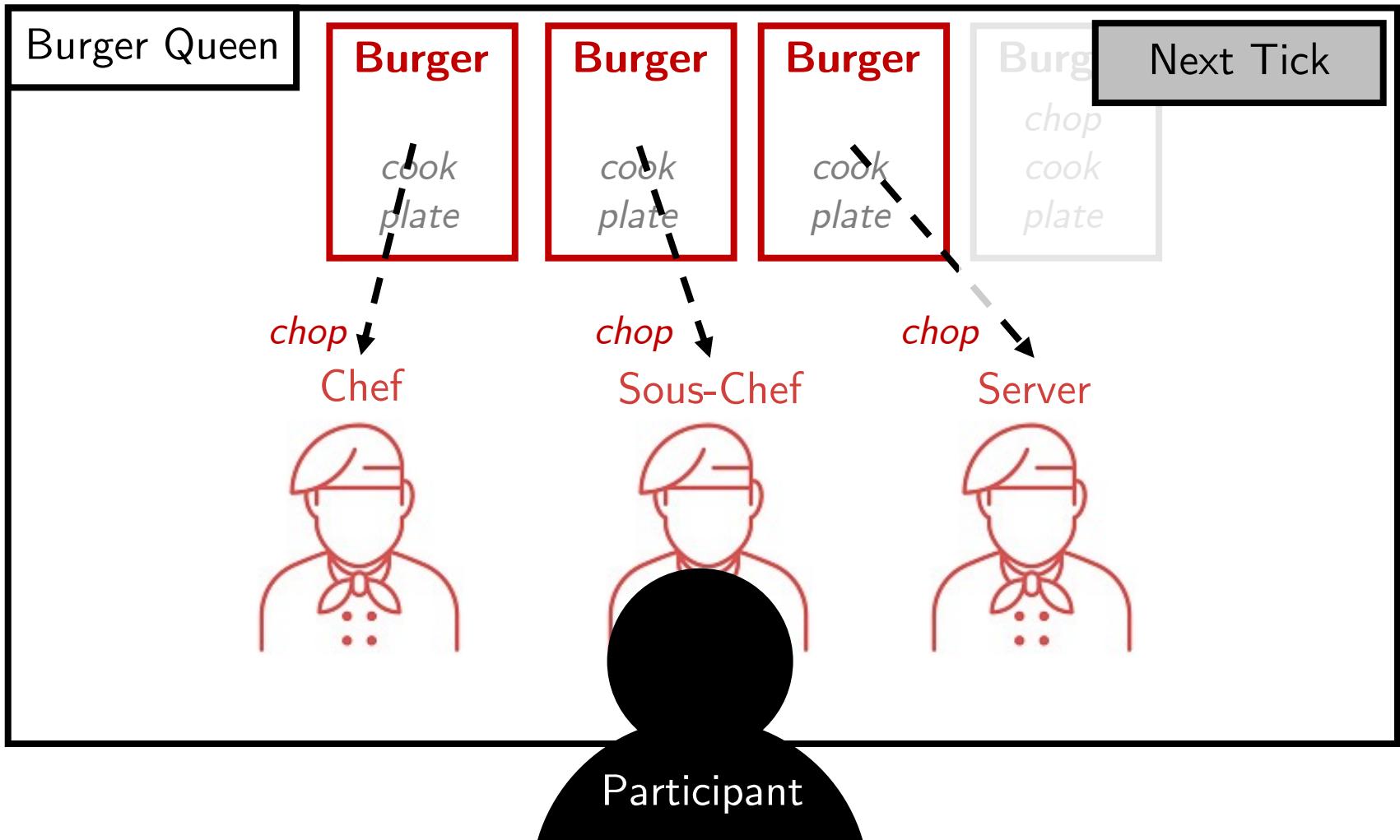
Queueing Game

Reward: 0
Tick #1/50



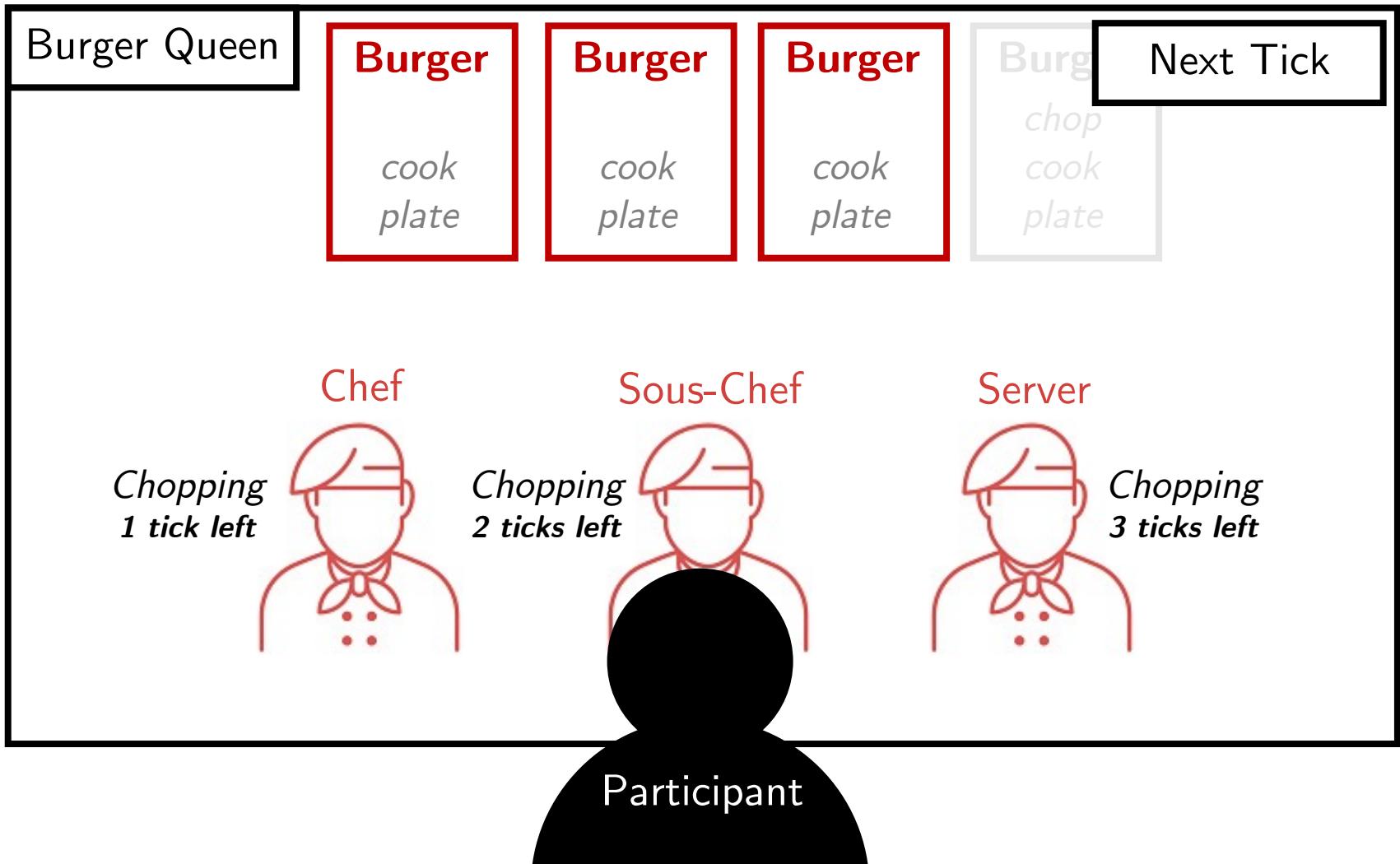
Queueing Game

Reward: 0
Tick #1/50



Queueing Game

Reward: 0
Tick #2/50



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



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

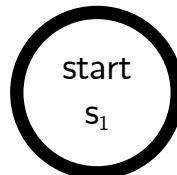
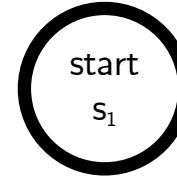
Problem Formulation

MDP Formulation:

Optimal policy and human make sequences of decisions



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

 π^*  π 

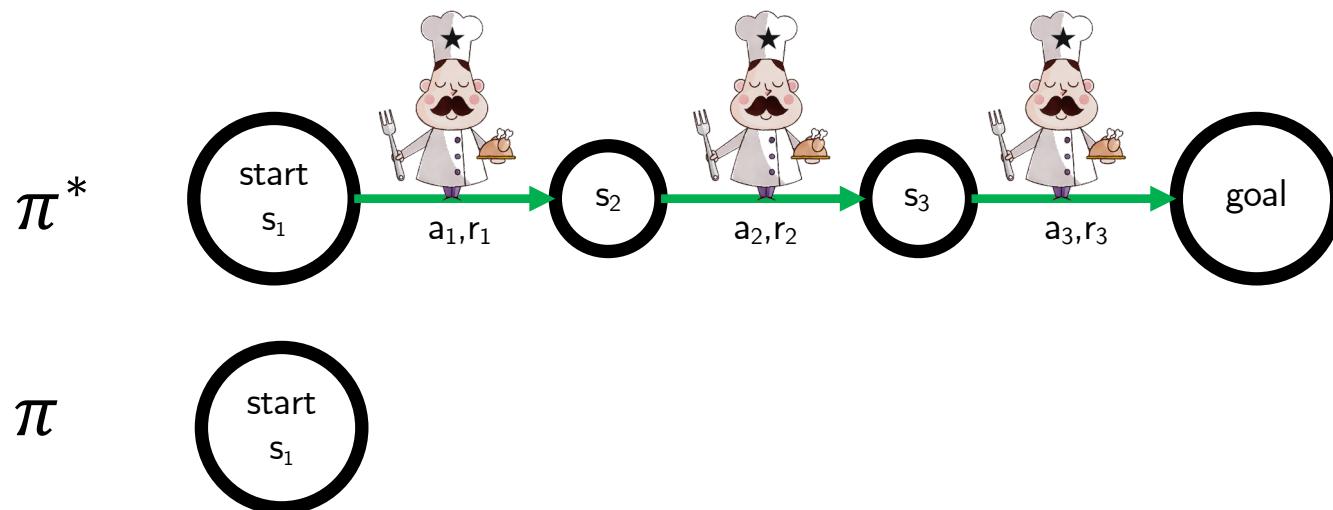
Problem Formulation

MDP Formulation:

Optimal policy and human make sequences of decisions



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



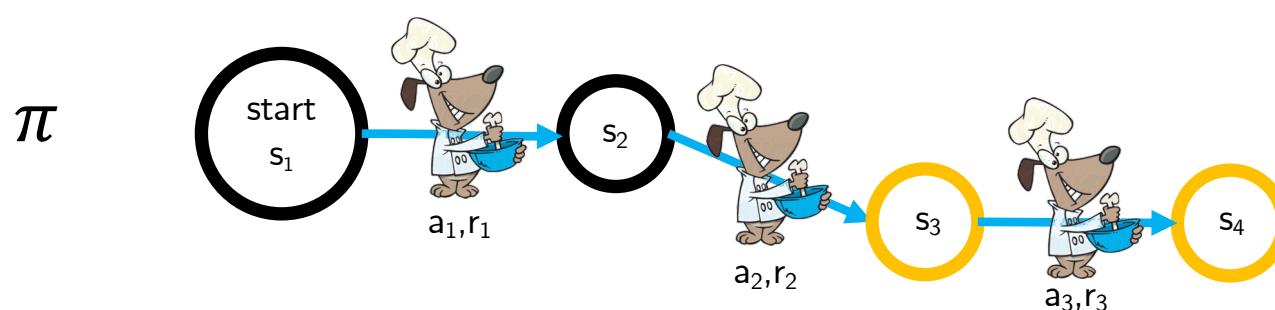
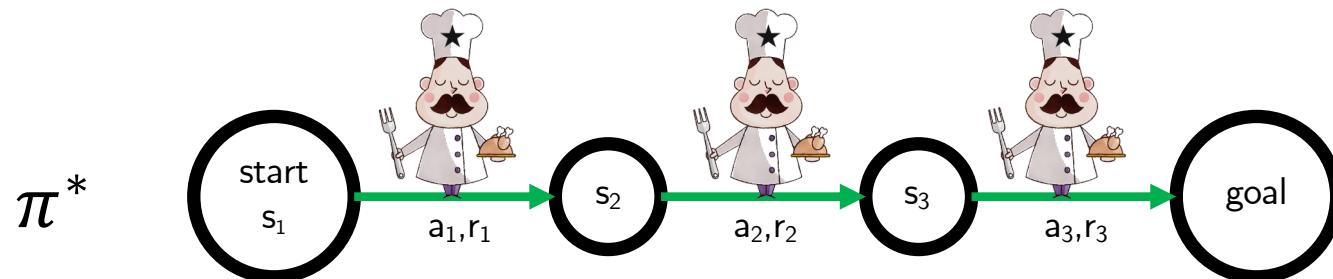
Problem Formulation

MDP Formulation:

Optimal policy and human make sequences of decisions

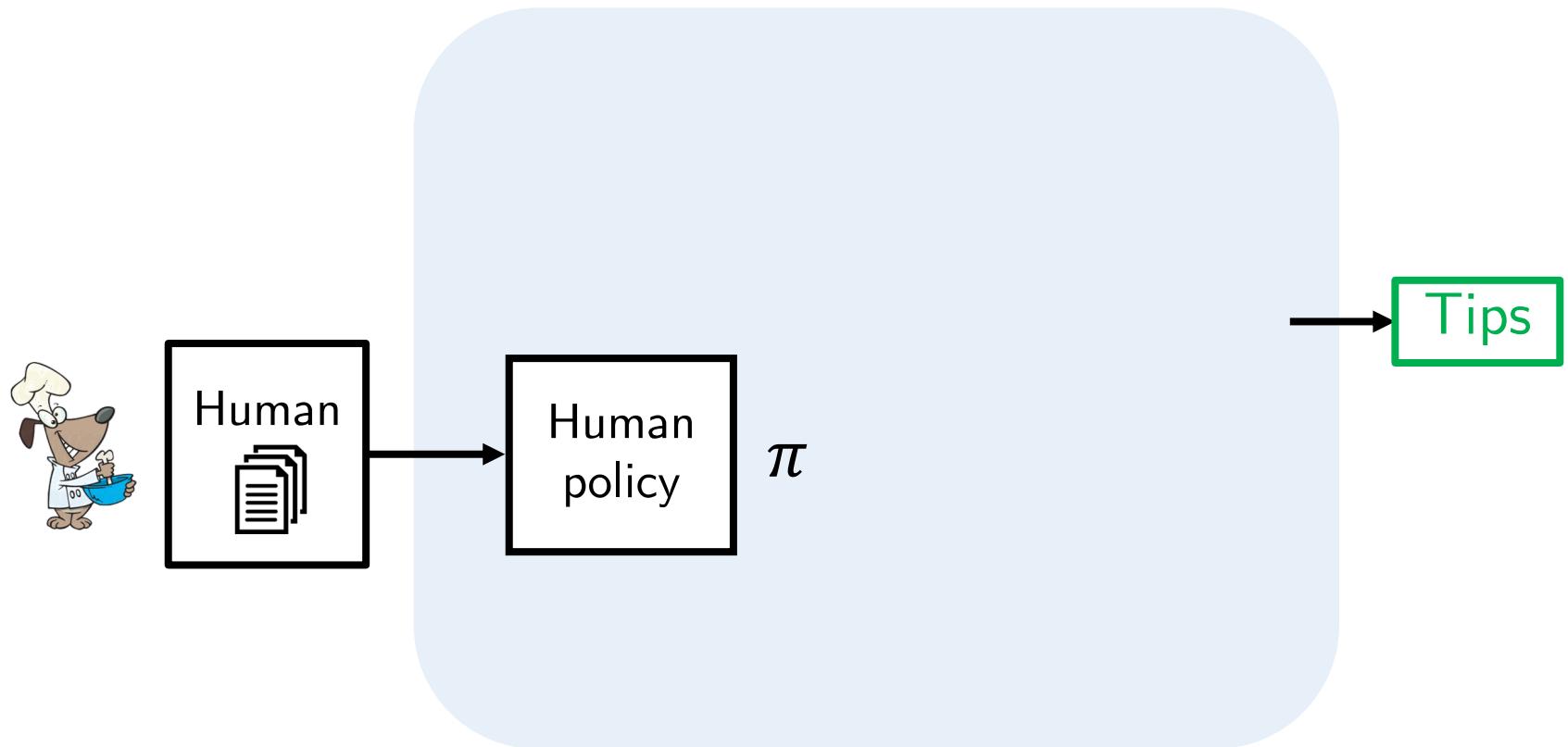


$$\mathcal{M} = (S, A, R, P, \gamma)$$



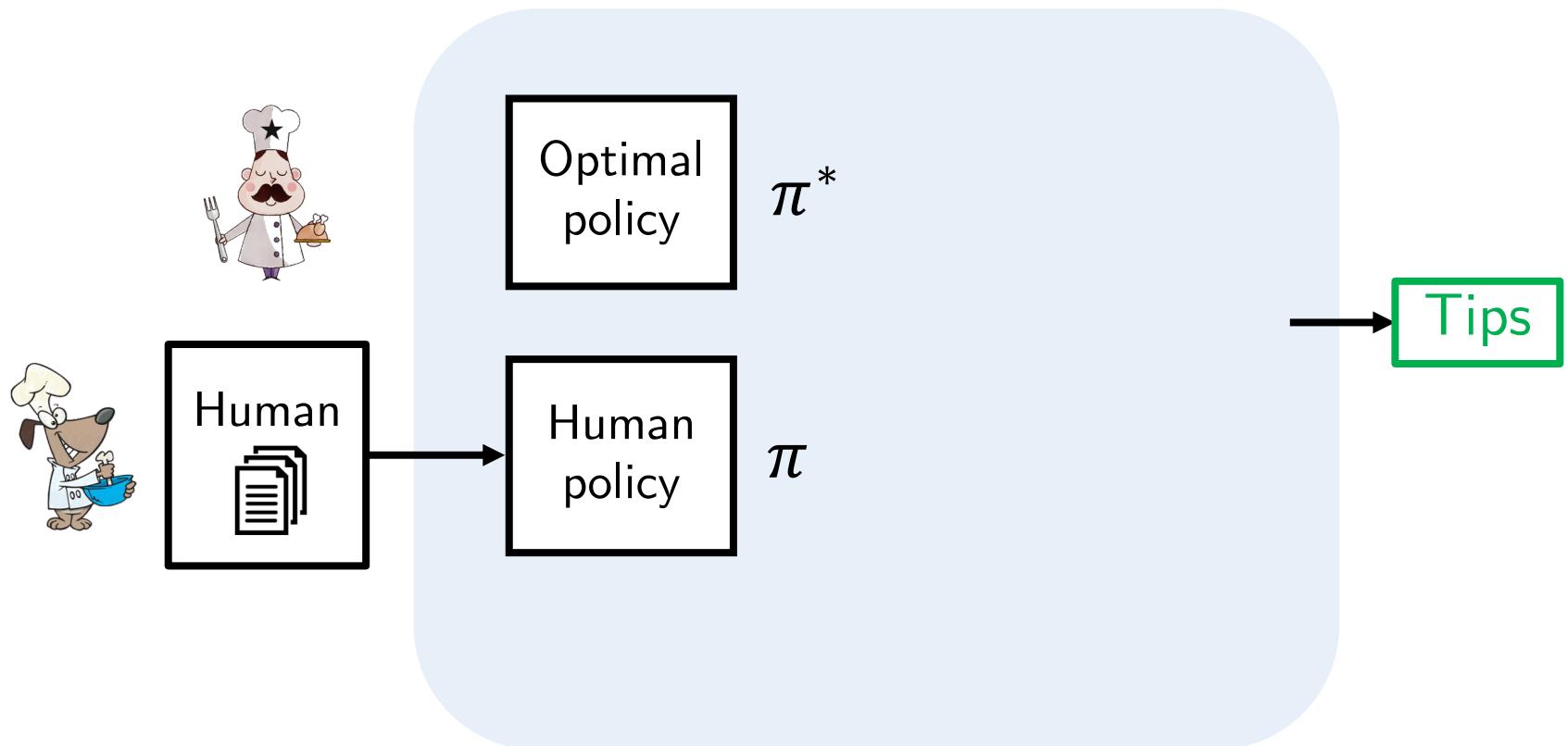
Our Approach

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



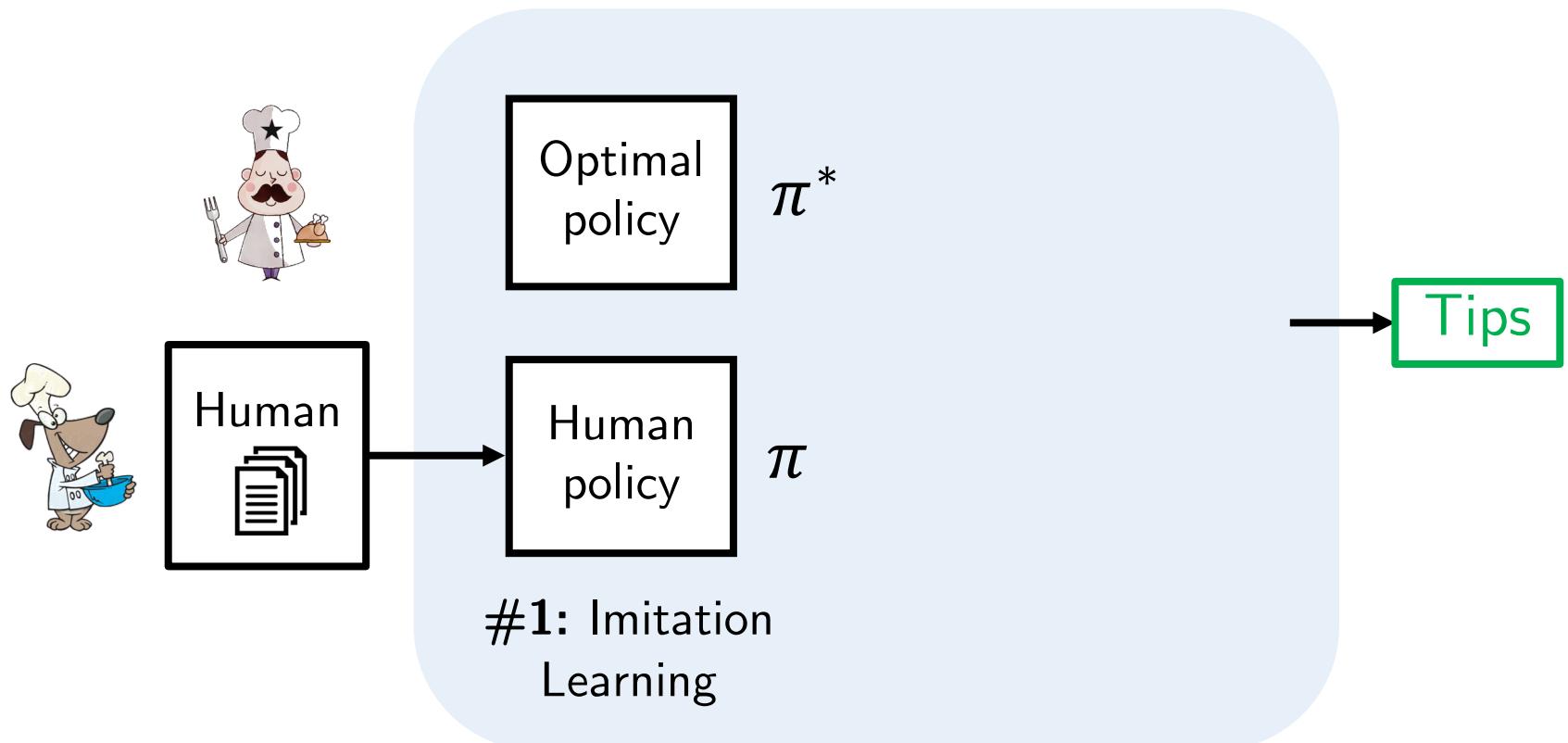
Our Approach

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



Our Approach

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



Ng & Russell 2000, Abbeel & Ng 2004,
Ziebart et al. 2008, Ross & Bagnell 2011

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

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

Step 1: Imitation Learning

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: Imitation Learning

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

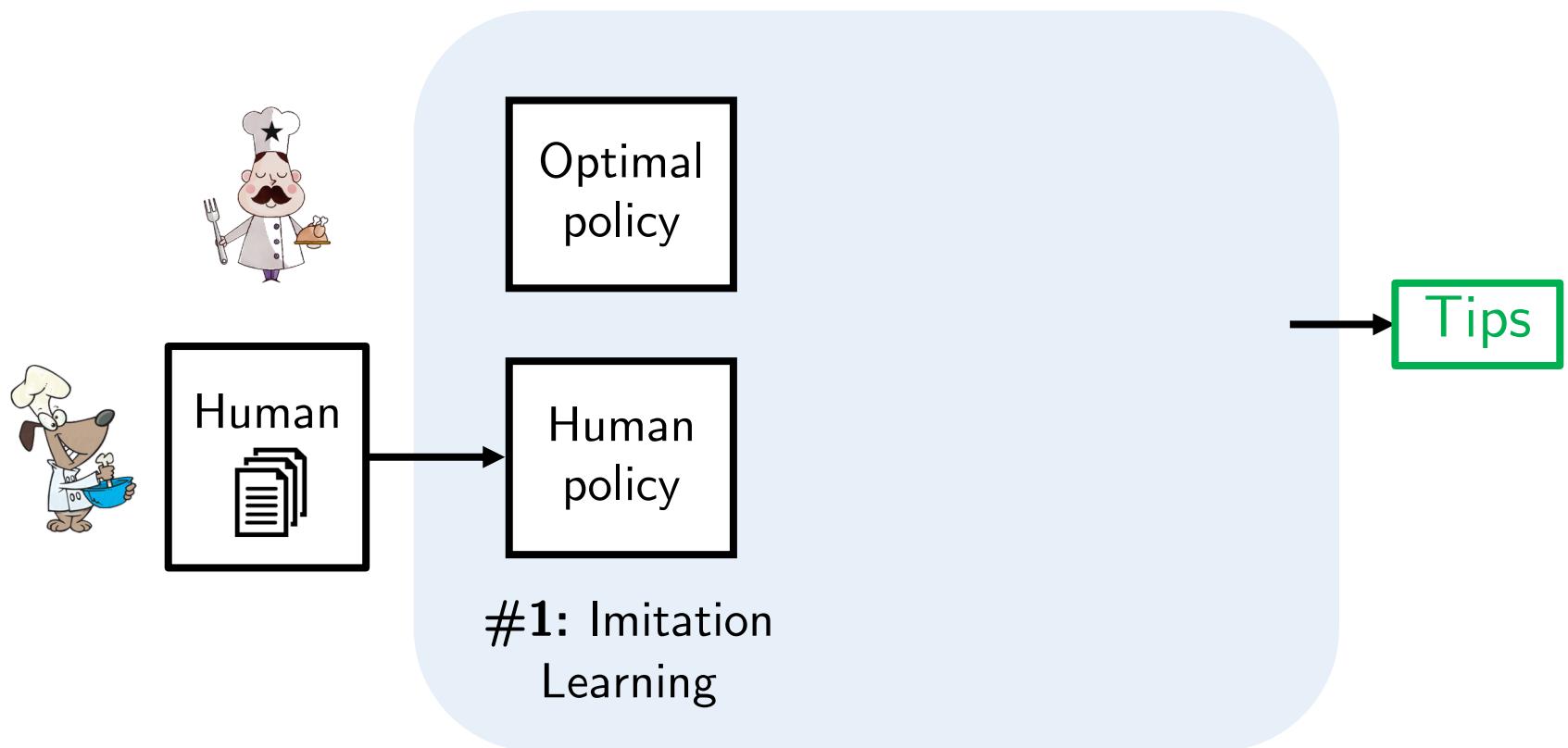
$$Q^\pi(s, a) = \mathbb{E}_{s' \sim p(s'|s, a)}[V^\pi(s')]$$

- Watkins & Dayan 1992

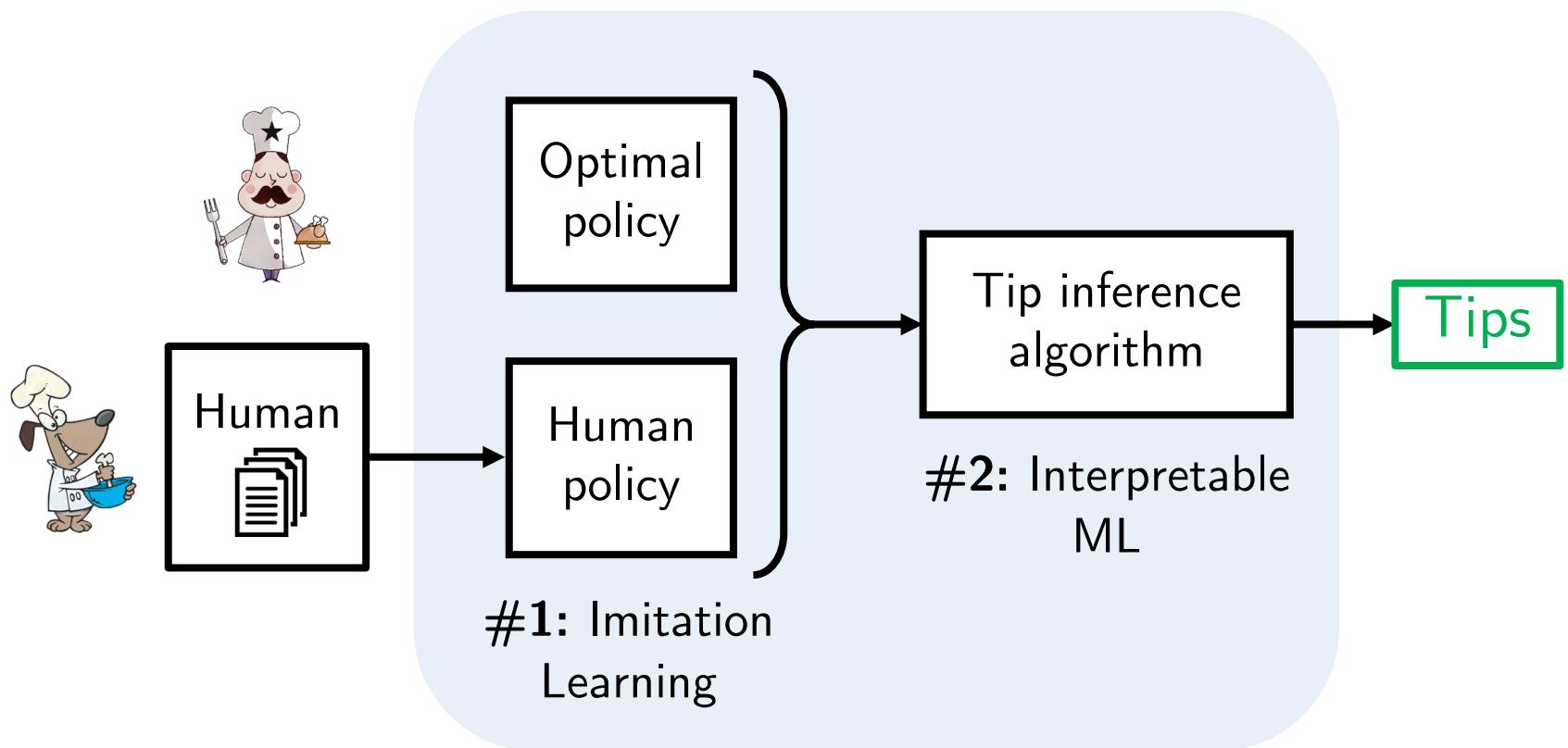
- Learn using supervised learning on trace data obtained using π

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

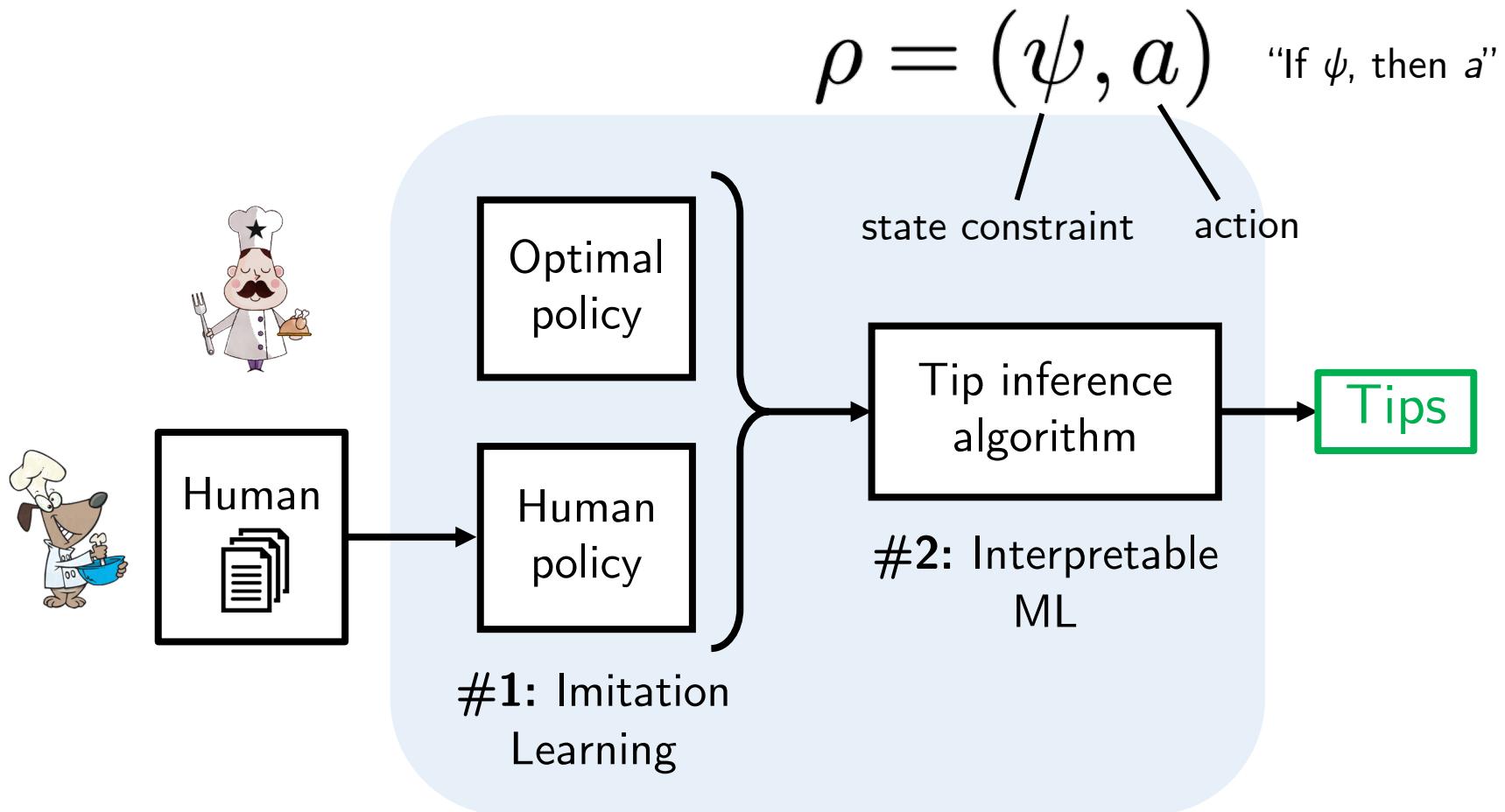
Our Approach



Our Approach



Our Approach



Step 2: Interpretable RL

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

$$J(\rho) = V^{\pi_h \oplus \rho}(s_0) - V^{\pi_h}(s_0)$$

Human policy + tip **Only human policy**

- $\pi_h \oplus \rho$ denotes overriding the human policy with tip ρ .
- J measures the improvement in human reward

Step 2: Interpretable RL

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

$$J(\rho) = V^{\pi_h \oplus \rho}(s_0) - V^{\pi_h}(s_0)$$

Human policy + tip **Only human policy**

- $\pi_h \oplus \rho$ denotes overriding the human policy with tip ρ .
 - J measures the improvement in human reward
-
- **Challenge:** Hard to estimate $V^{\pi_h \oplus \rho}$

Step 2: Interpretable RL

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

$$J(\rho) = V^{\pi_h \oplus \rho}(s_0) - V^{\pi_h}(s_0)$$

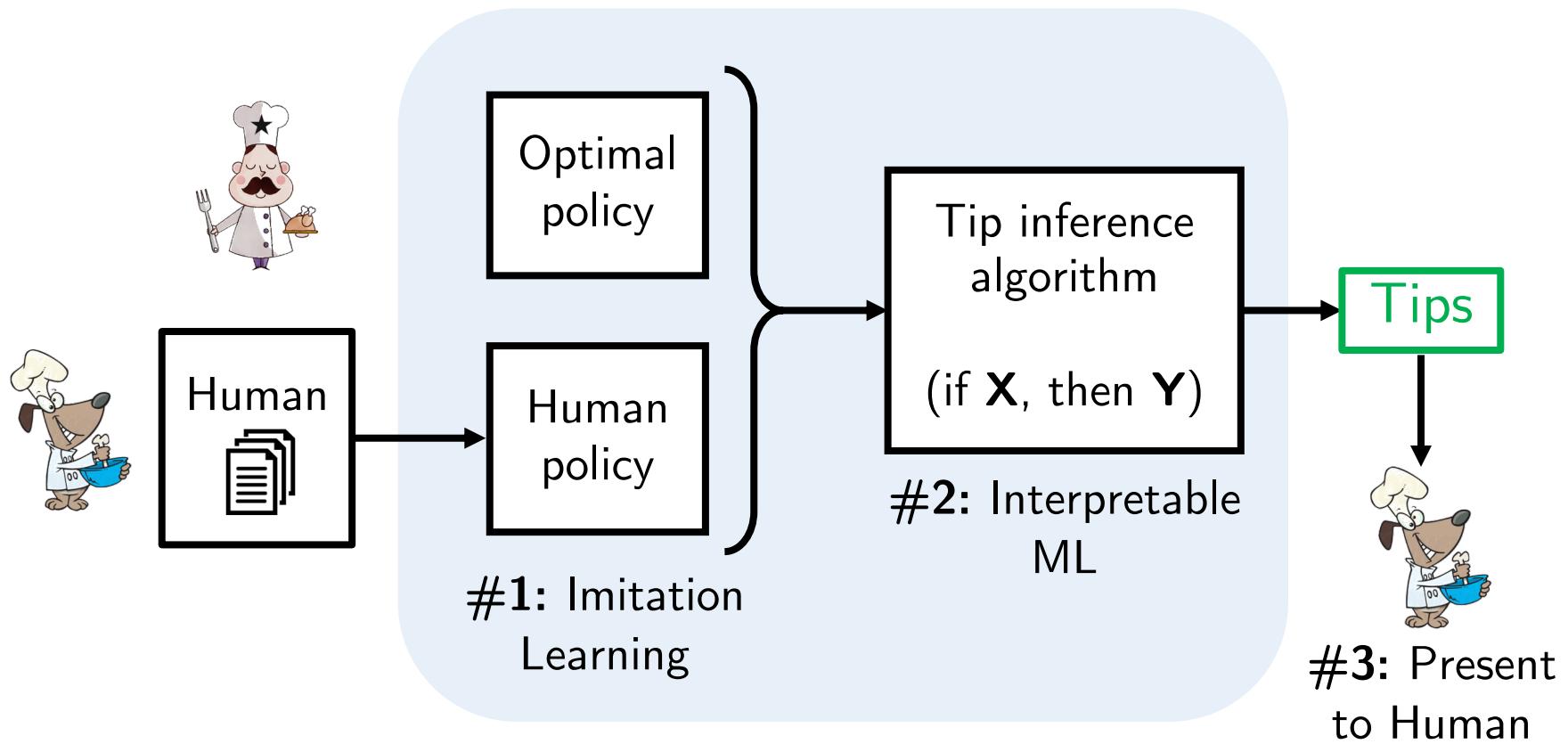
Human policy + tip **Only human policy**

- $\pi_h \oplus \rho$ denotes overriding the human policy with tip ρ .
- J measures the improvement in human reward
- **Challenge:** Hard to estimate $V^{\pi_h \oplus \rho}$
- **Key Lemma:**

$$J(\rho) \approx \mathbb{E}_{(s,a) \sim D_{\pi_h \oplus \rho}} [Q^*(s, a \oplus \rho) - Q^*(s, a)]$$

- Q^* is the optimal policy's Q function
- D_π is the state-action distribution of policy π
- $a \oplus \rho$ overrides the human action a if the tip is applicable in state s

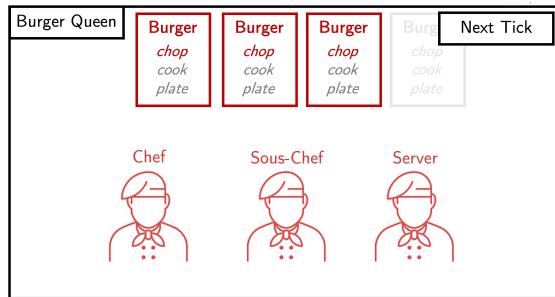
Our Approach



User Study Design

Phase I

N = 200

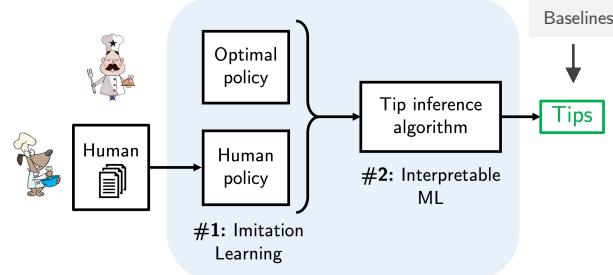
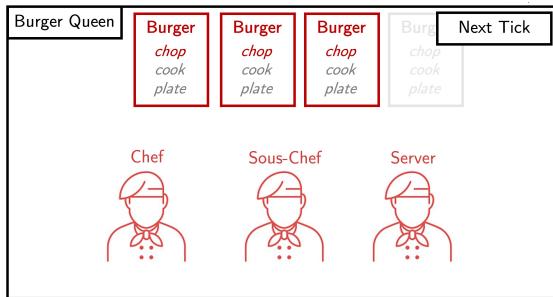


Gather trace data

User Study Design

Phase I

N = 200



Gather trace data

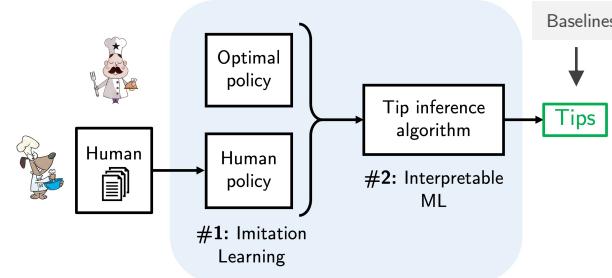
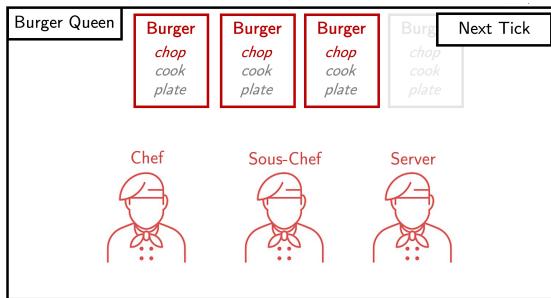
Tip inference

User Study Design

N = 1400

Phase I

N = 200

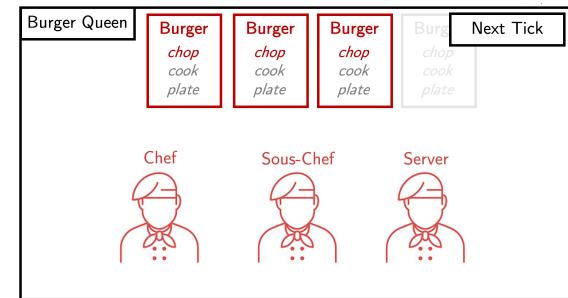


Gather trace data

Tip inference

Phase II

Tip: [randomly assigned tip here]



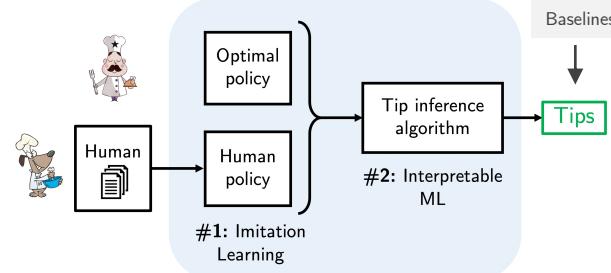
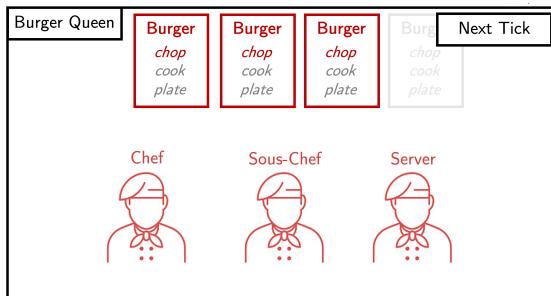
Tip evaluation

User Study Design

N = 1400

Phase I

N = 200

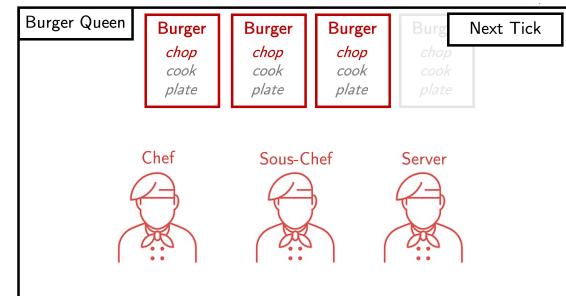


Gather trace data

Tip inference

Phase II

Tip: [randomly assigned tip here]



Tip evaluation

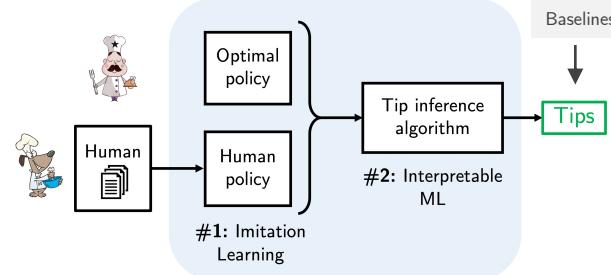
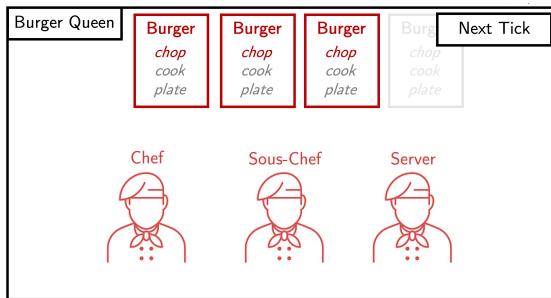
Environment

User Study Design

N = 1400

Phase I

N = 200

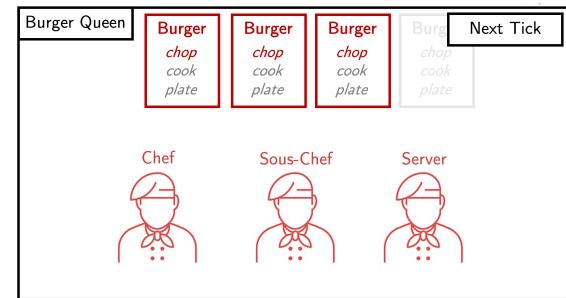


Gather trace data

Tip inference

Phase II

Tip: [randomly assigned tip here]



Tip evaluation

Environment

Normal

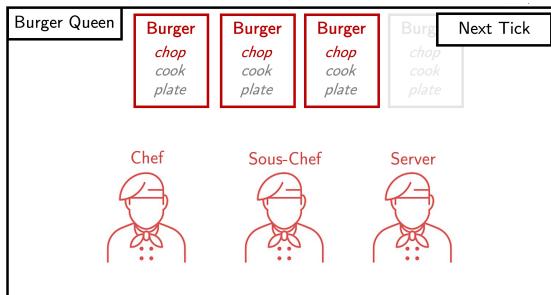


User Study Design

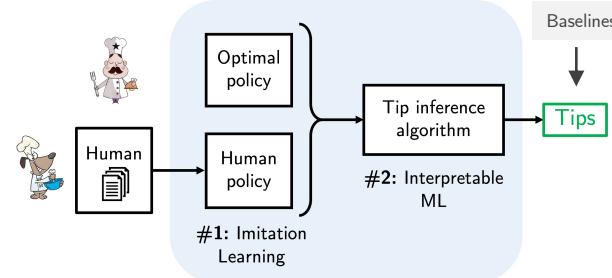
N = 1400

Phase I

N = 200



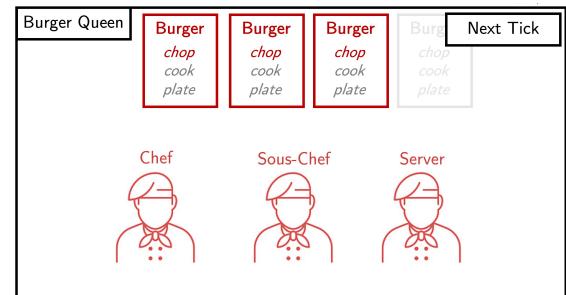
Gather trace data



Tip inference

Phase II

Tip: [randomly assigned tip here]



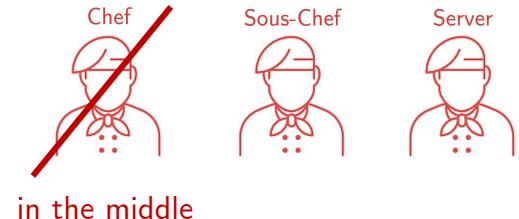
Tip evaluation

Environment

Normal



Disrupted



Design Tip Inference

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

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

Design Tip Inference

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

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

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

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

Design Tip Inference

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

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

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

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



Assign cooking to chef 2 times

Design Tip Inference

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

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

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

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



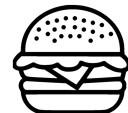
Assign cooking to chef 2 times



Chef should cook twice

Design

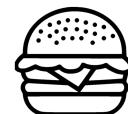
Disrupted Configuration



x 4 within 50 ticks

Design

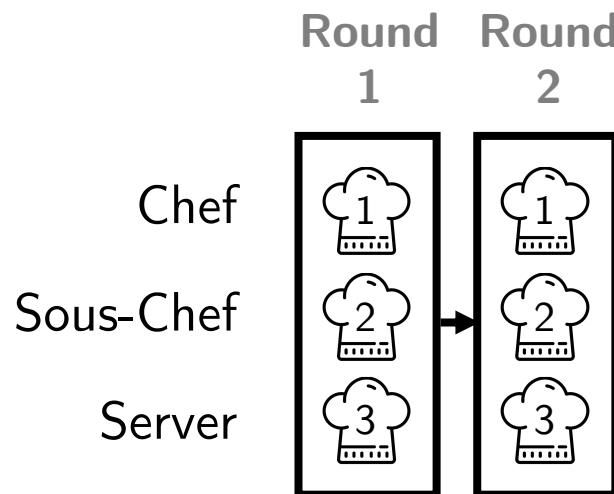
Disrupted Configuration



x 4 within 50 ticks

+ Our Tip

“Chef should never plate”

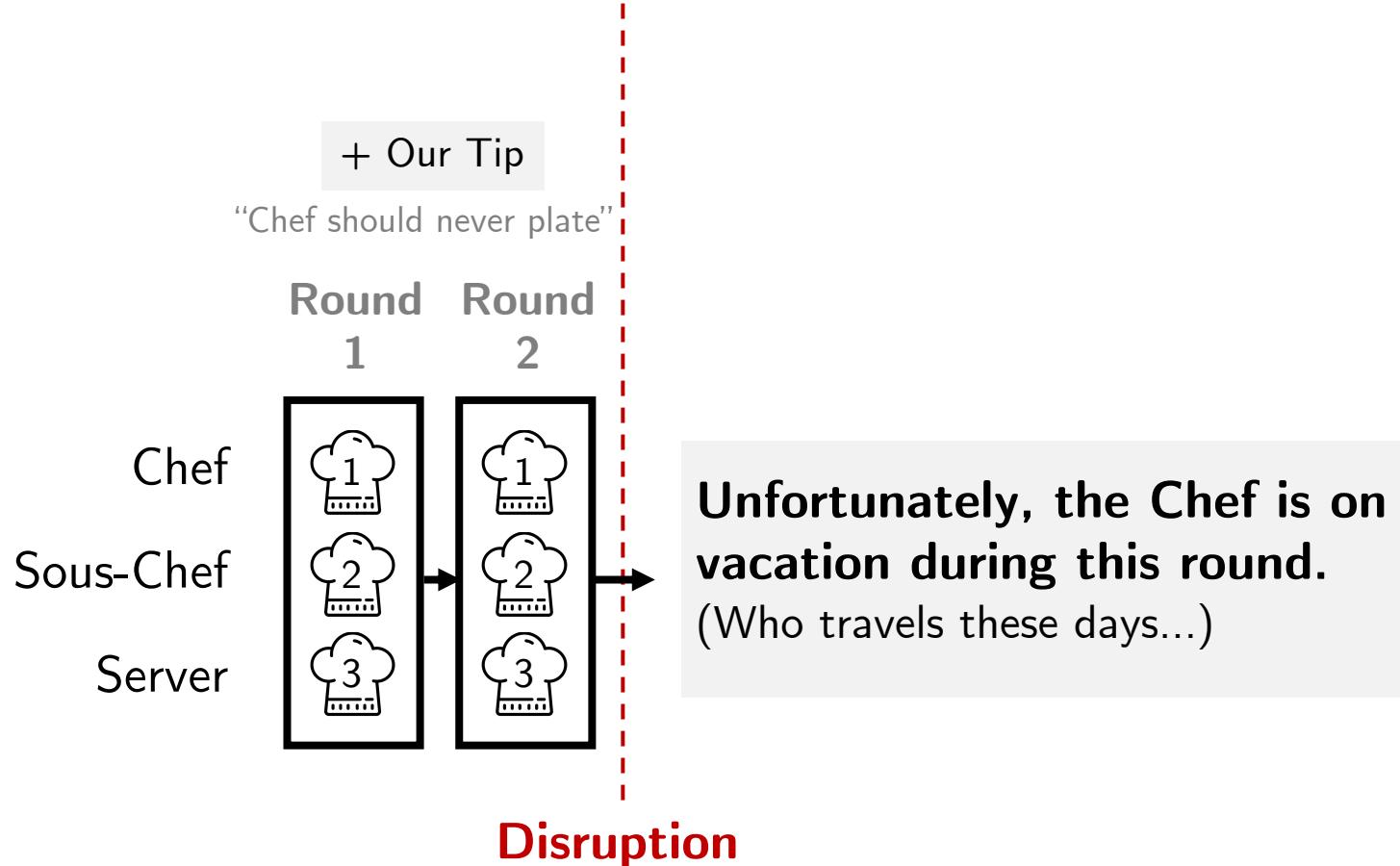


Design

Disrupted Configuration



x 4 within 50 ticks

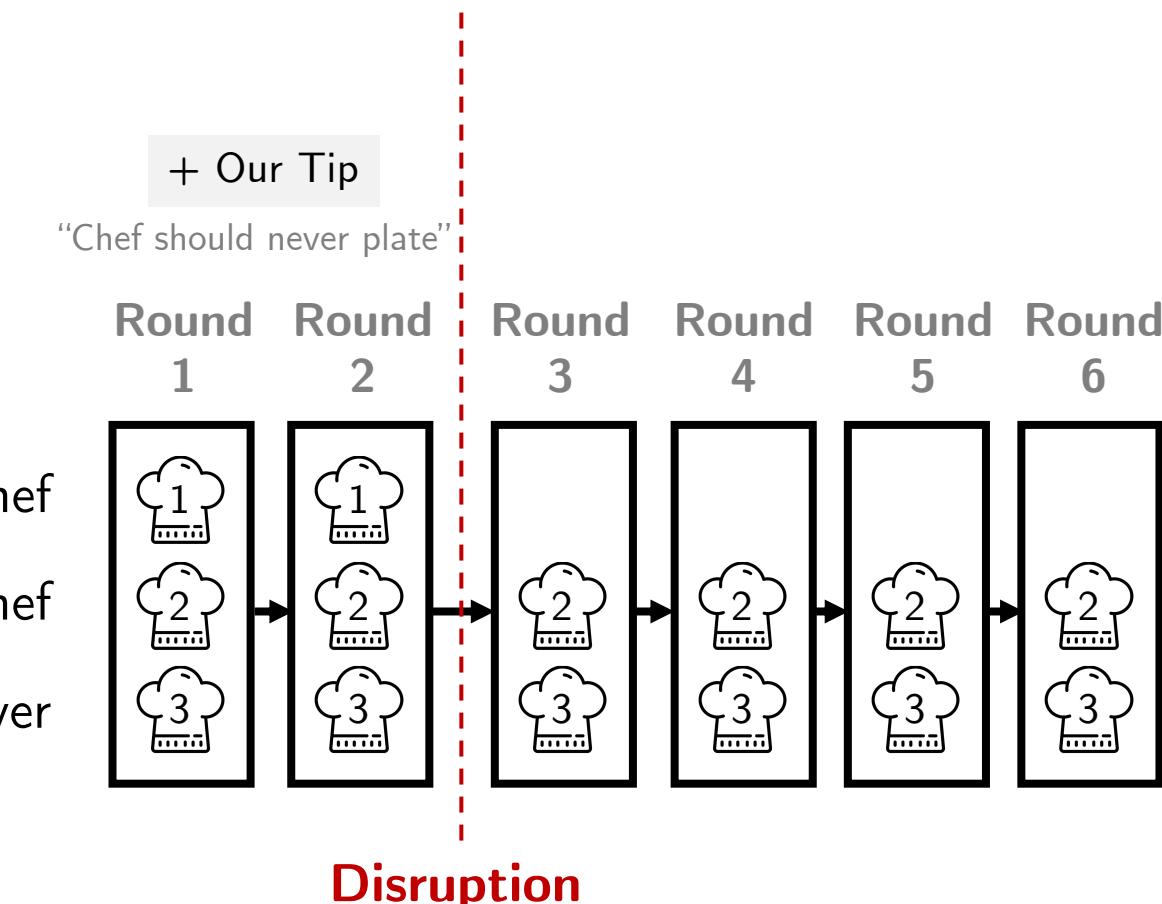


Design

Disrupted Configuration



x 4 within 50 ticks



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

Control

- No tip -

Algorithm

Server
should cook twice

Tip:

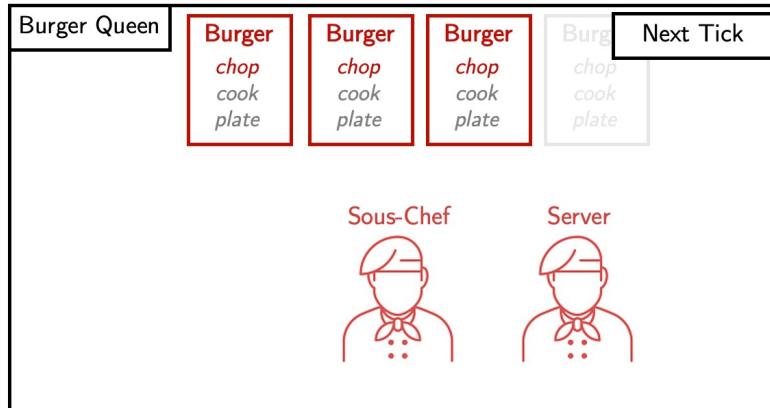
Human

Server
should cook once

Baseline

Sous-Chef
should plate twice

Reward: 0
Tick #1/50



Phase II

Algorithm vs Human

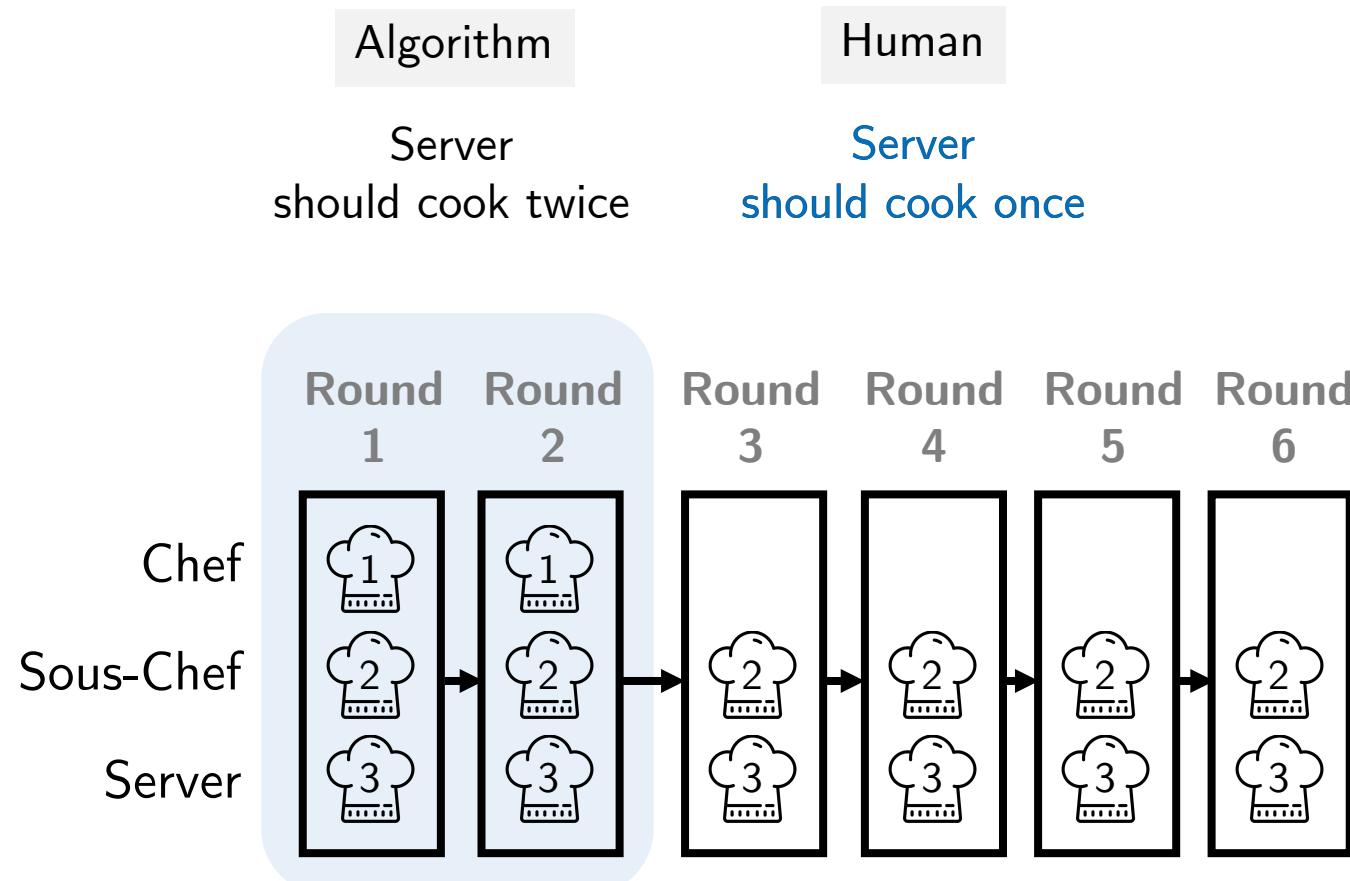
Algorithm

Server
should cook twice

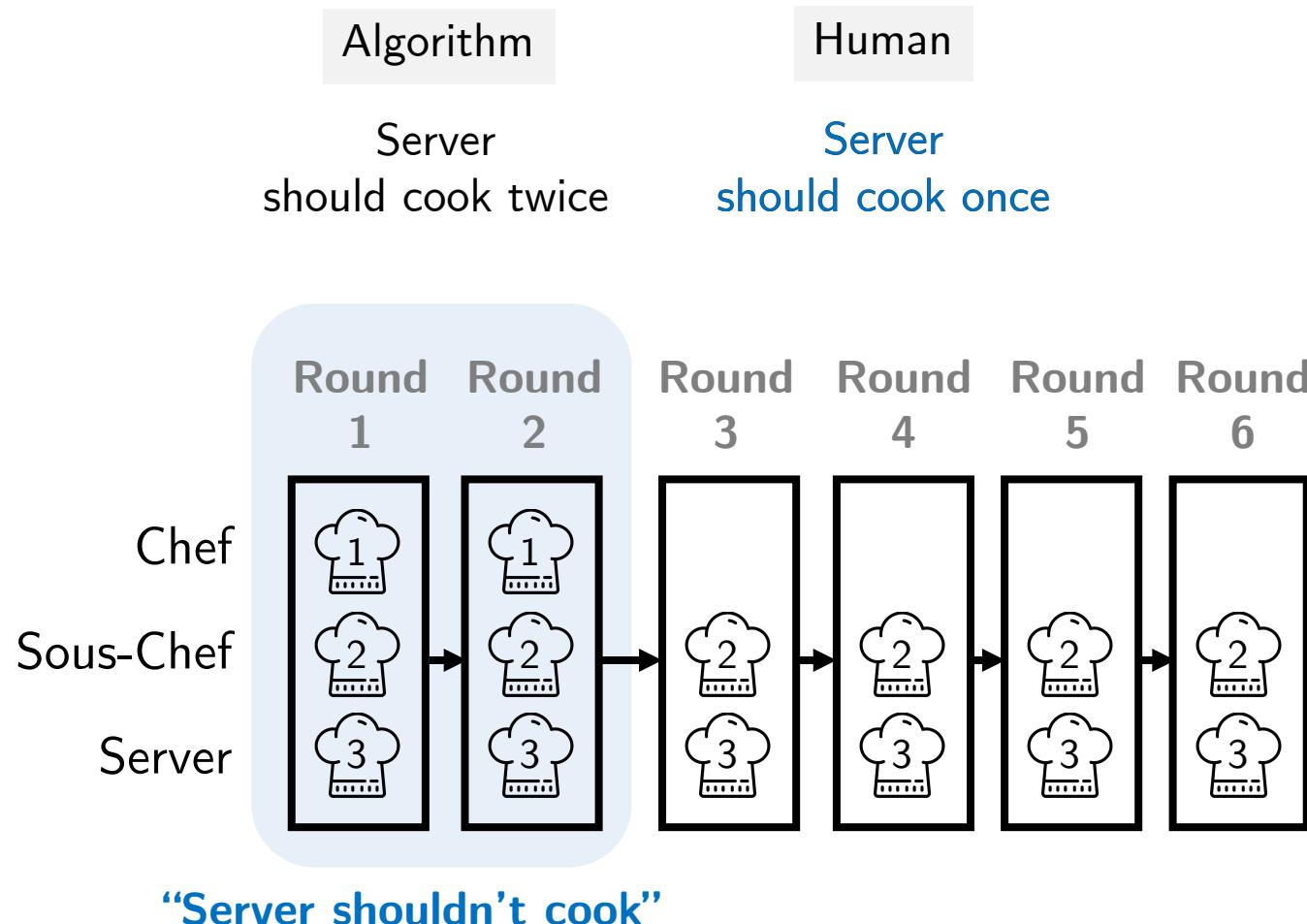
Human

Server
should cook once

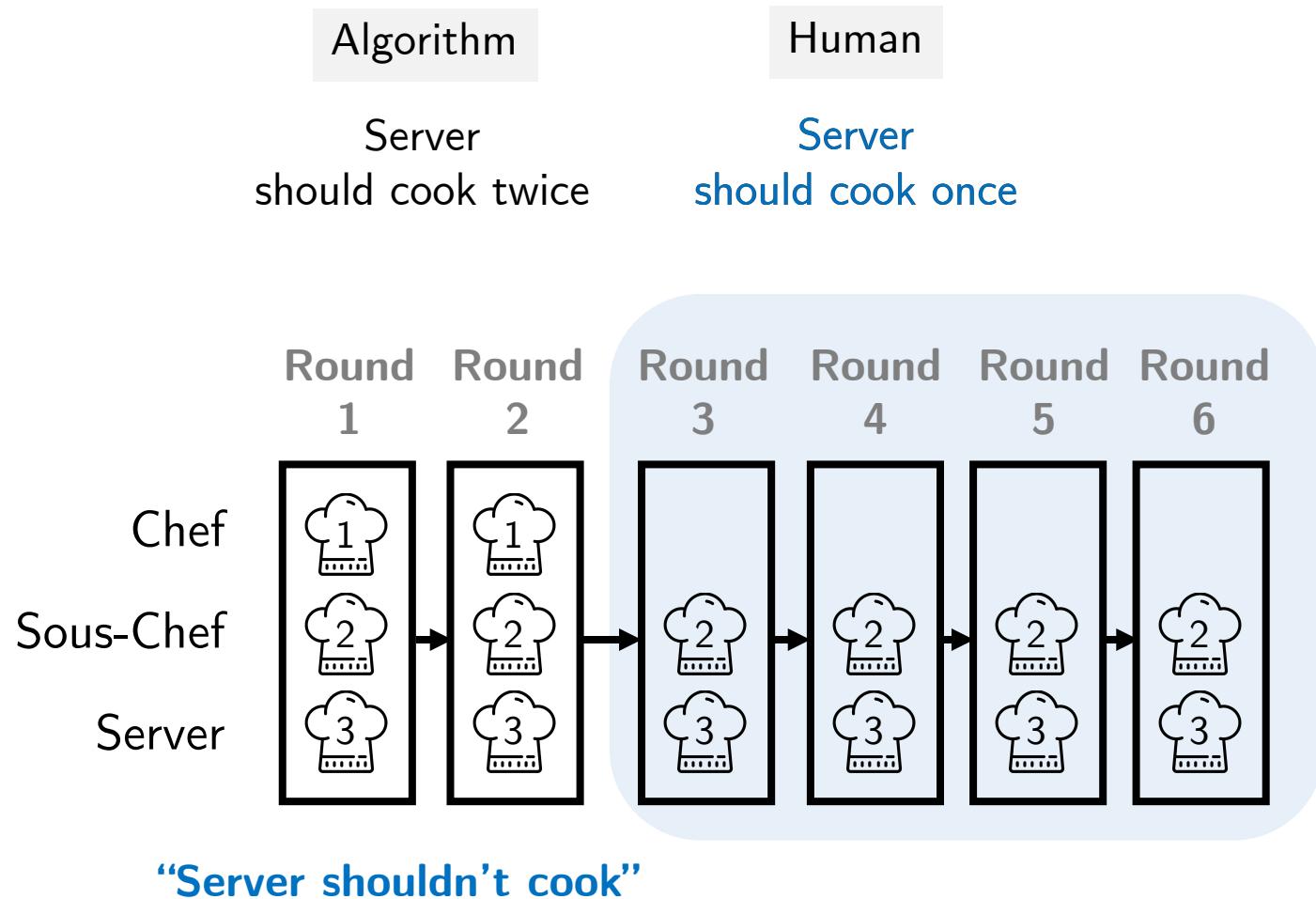
Algorithm vs Human



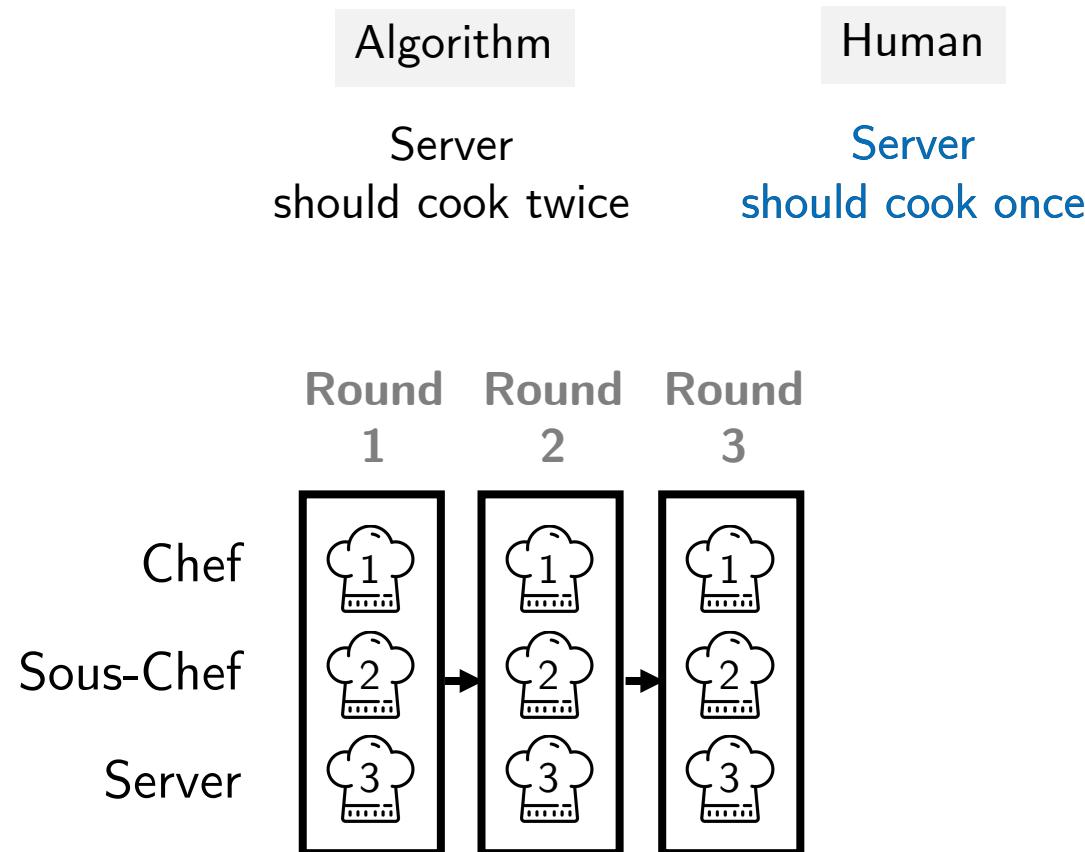
Algorithm vs Human



Algorithm vs Human

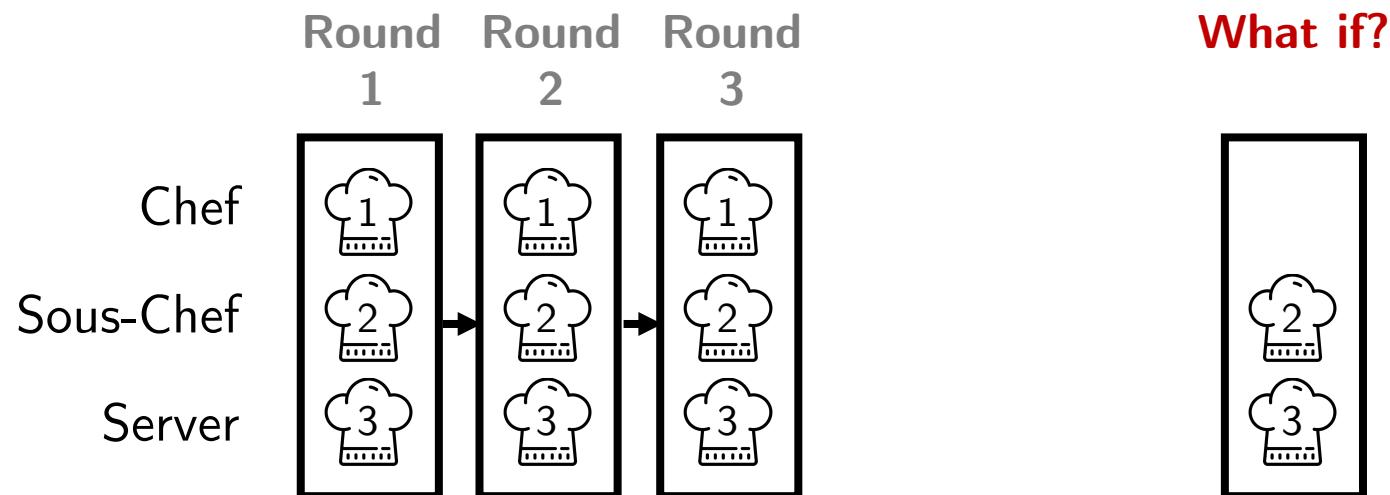


Algorithm vs Human



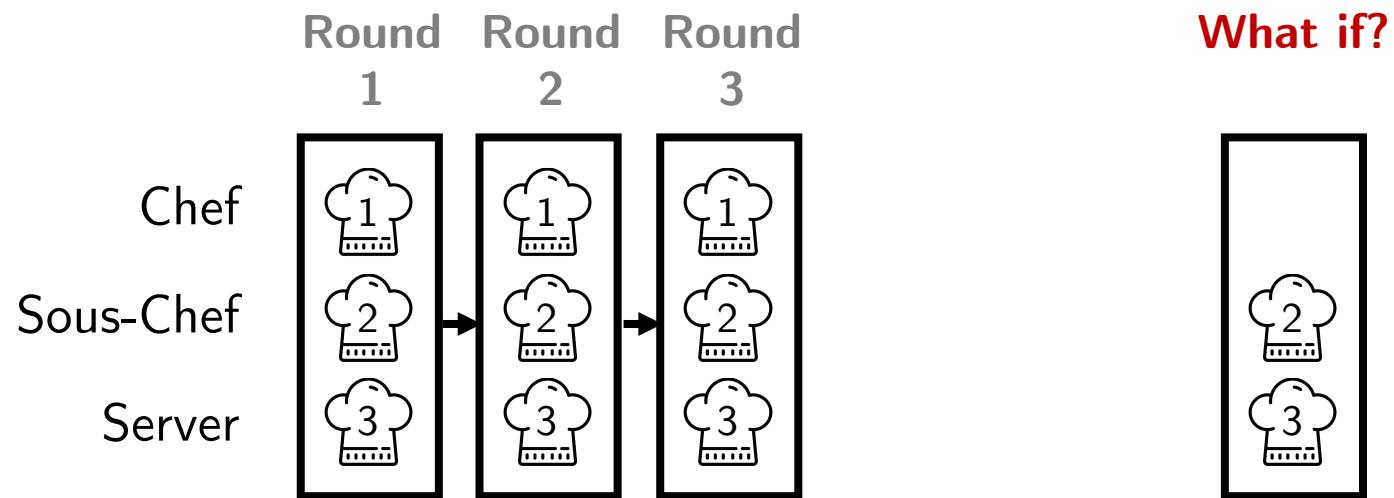
Algorithm vs Human

Algorithm	Human
Server should cook twice	Server should cook once

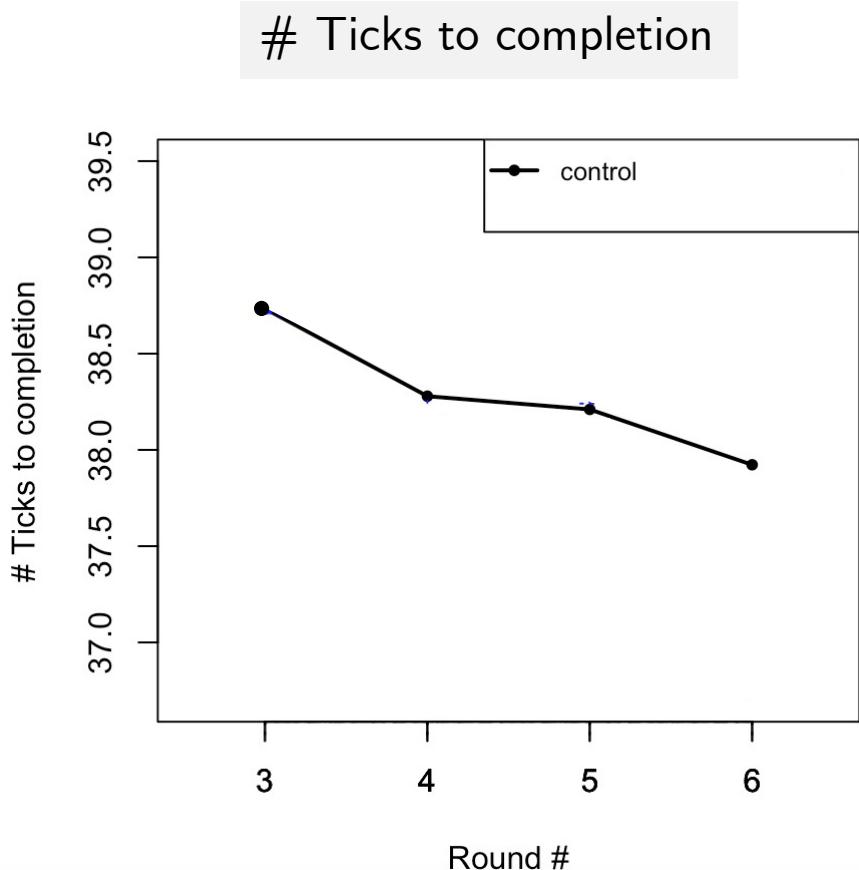


Algorithm vs Human

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



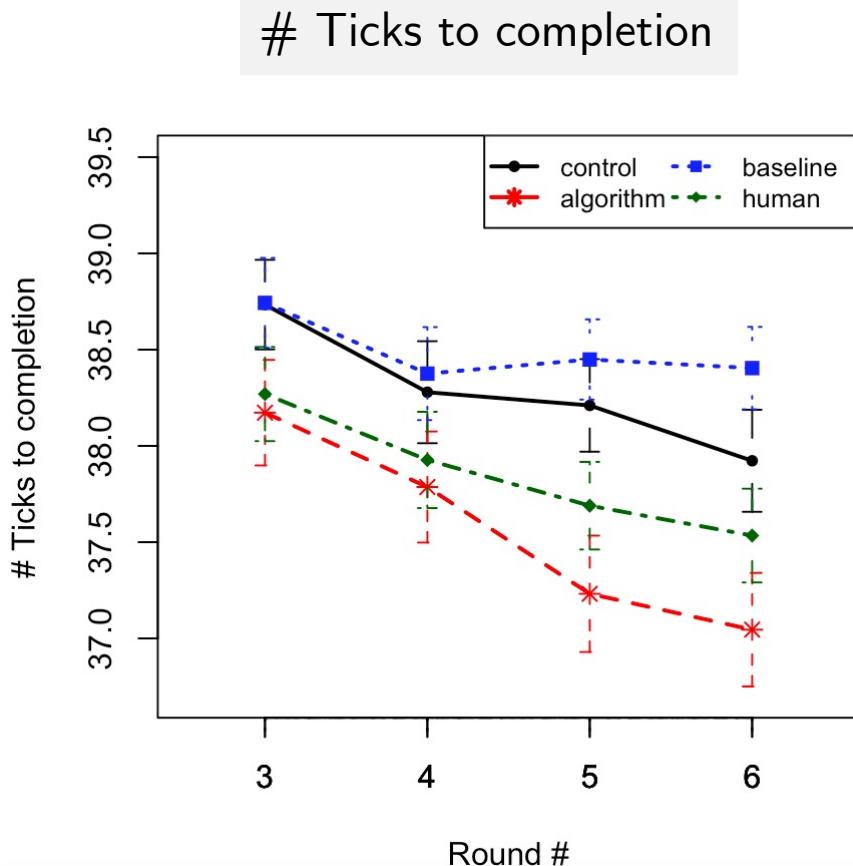
Results People Improve Over Time



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

Results

Our Tip Improves Performance



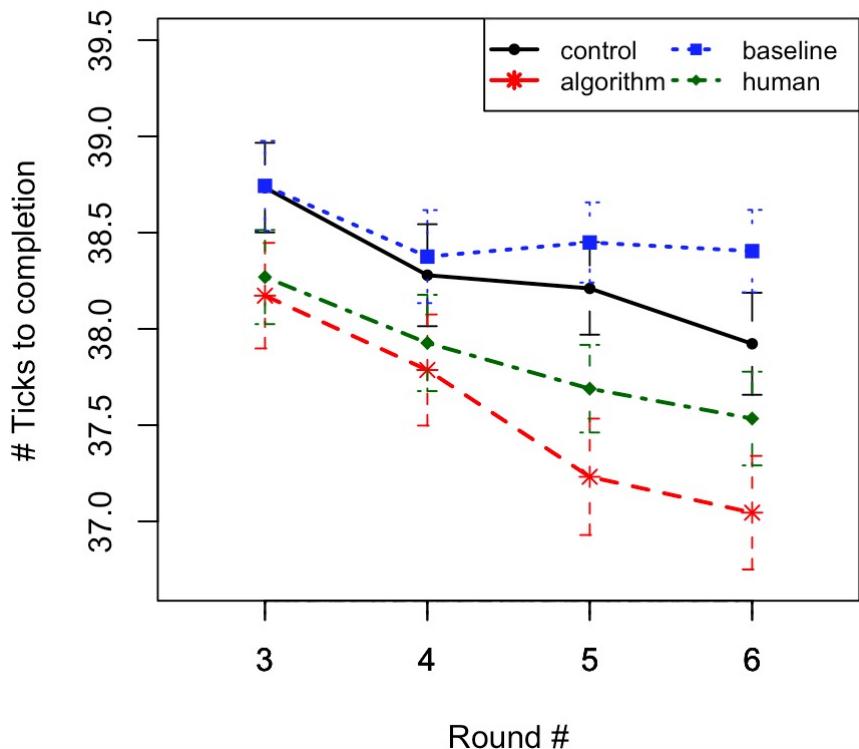
One-sided T-Tests

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

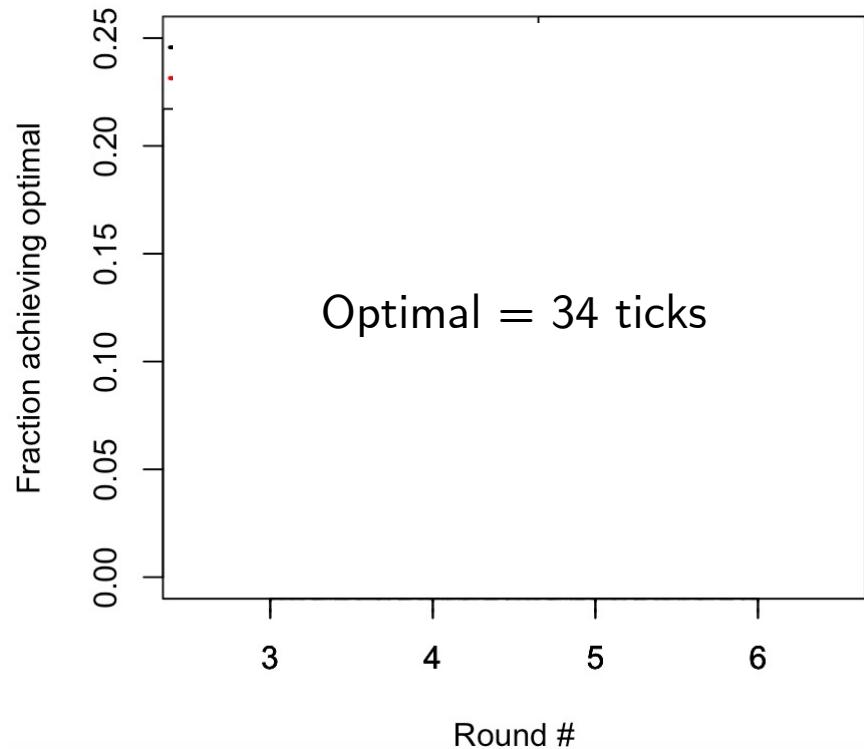
Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

Results

Ticks to completion



Fraction achieving optimal

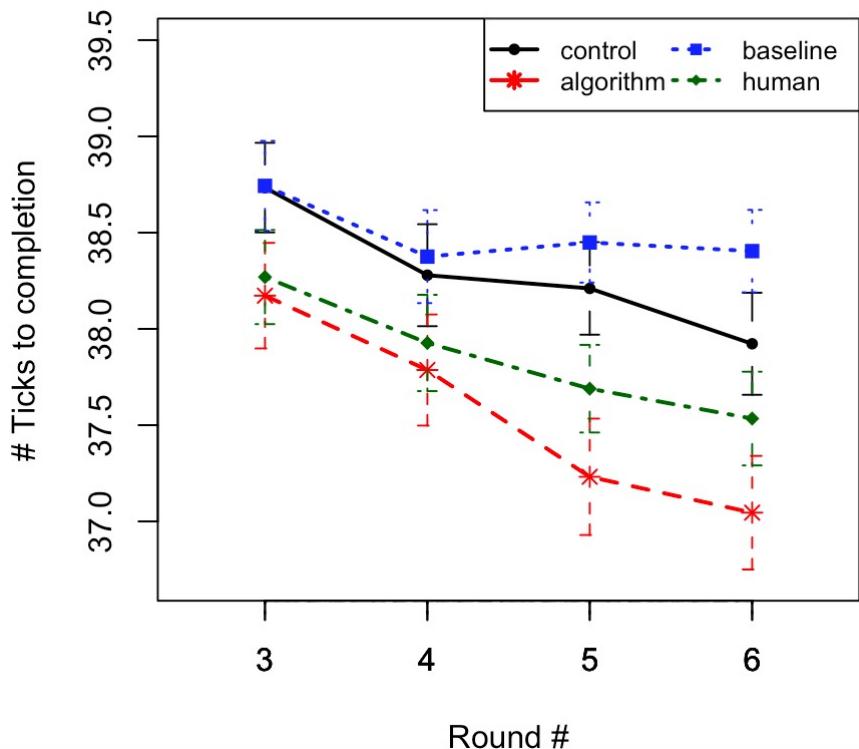


Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

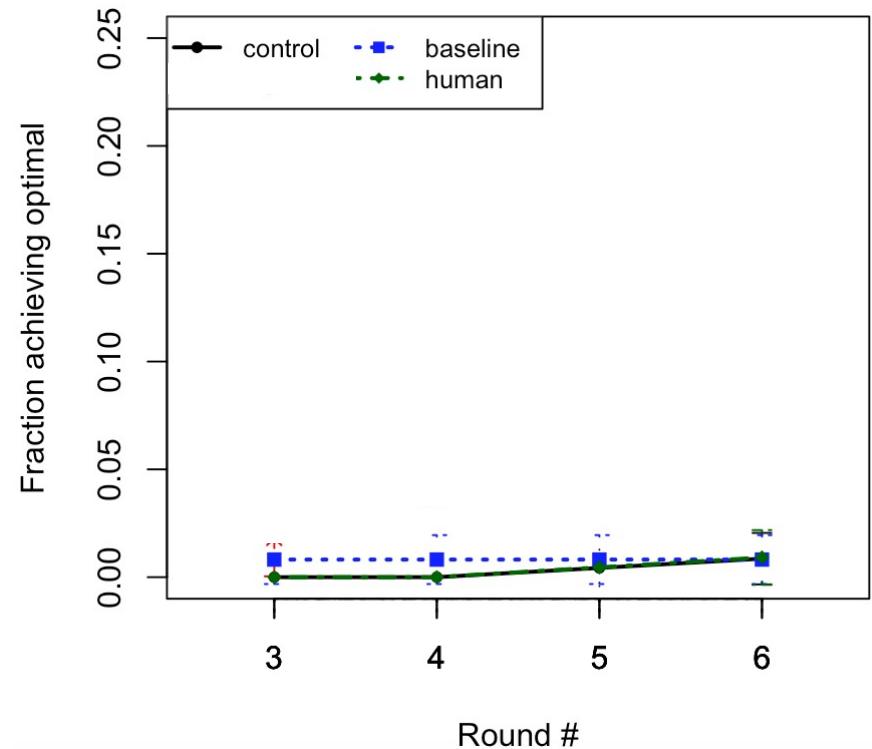
Results

Difficult to Reach Optimal

Ticks to completion



Fraction achieving optimal

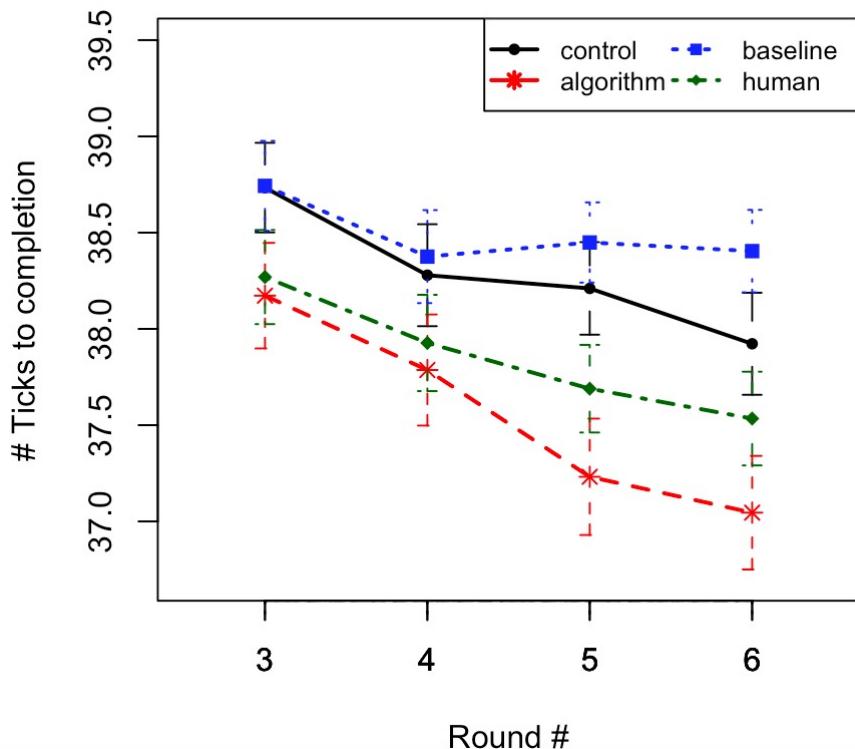


Amazon Mechanical Turk, N = 1,011
mean age 34.9, 60% female

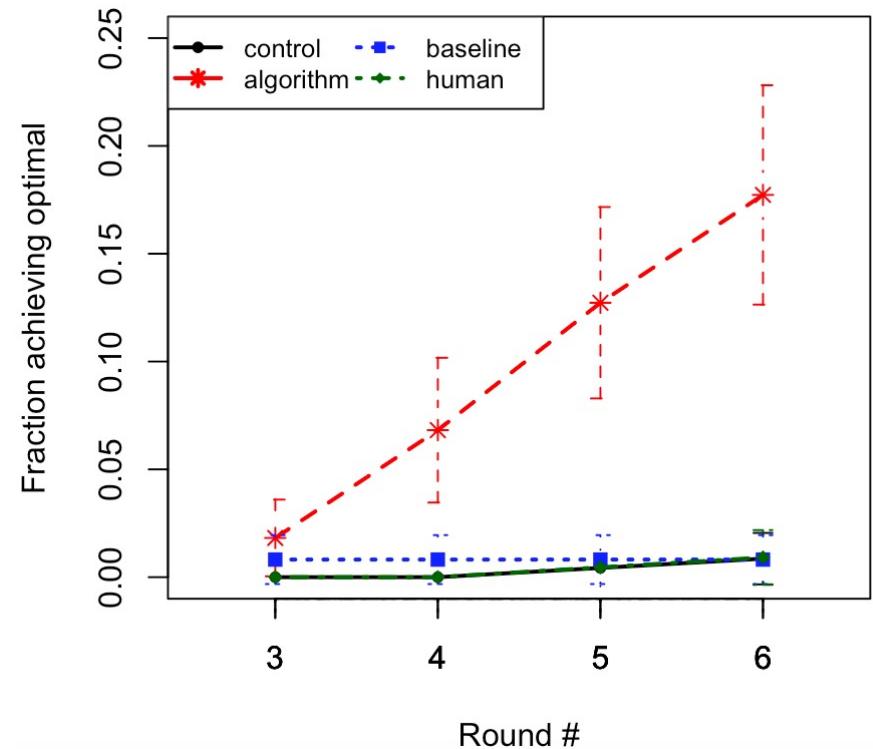
Results

Our Tip Helps Reach Optimal

Ticks to completion



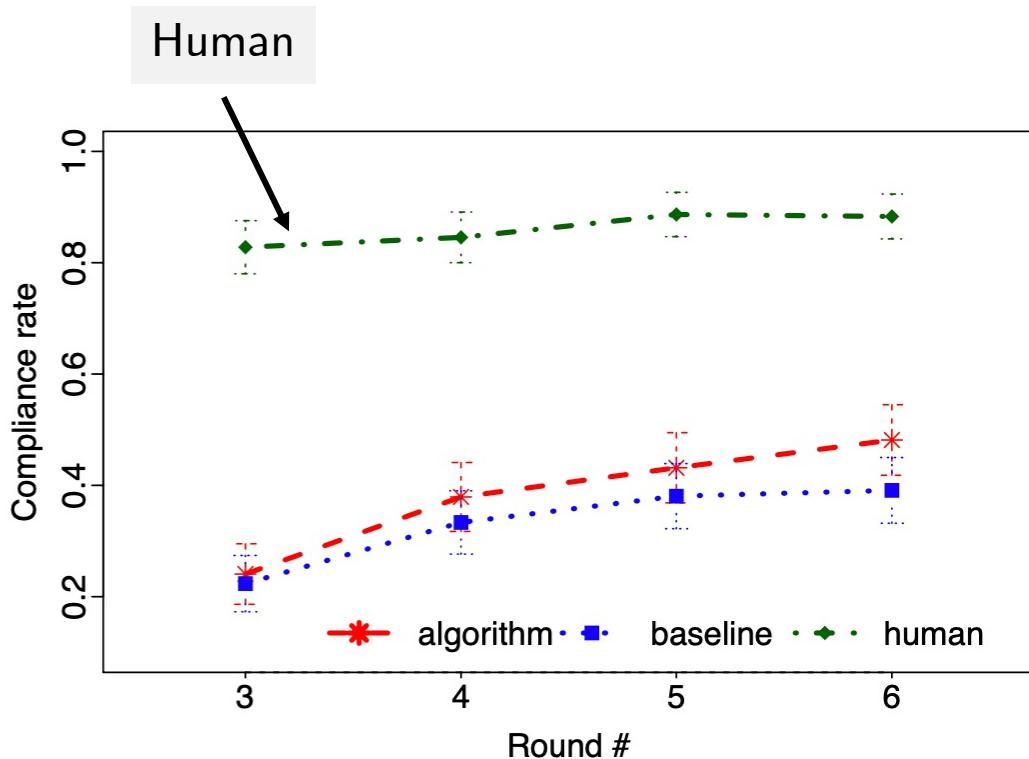
Fraction achieving optimal



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

Results

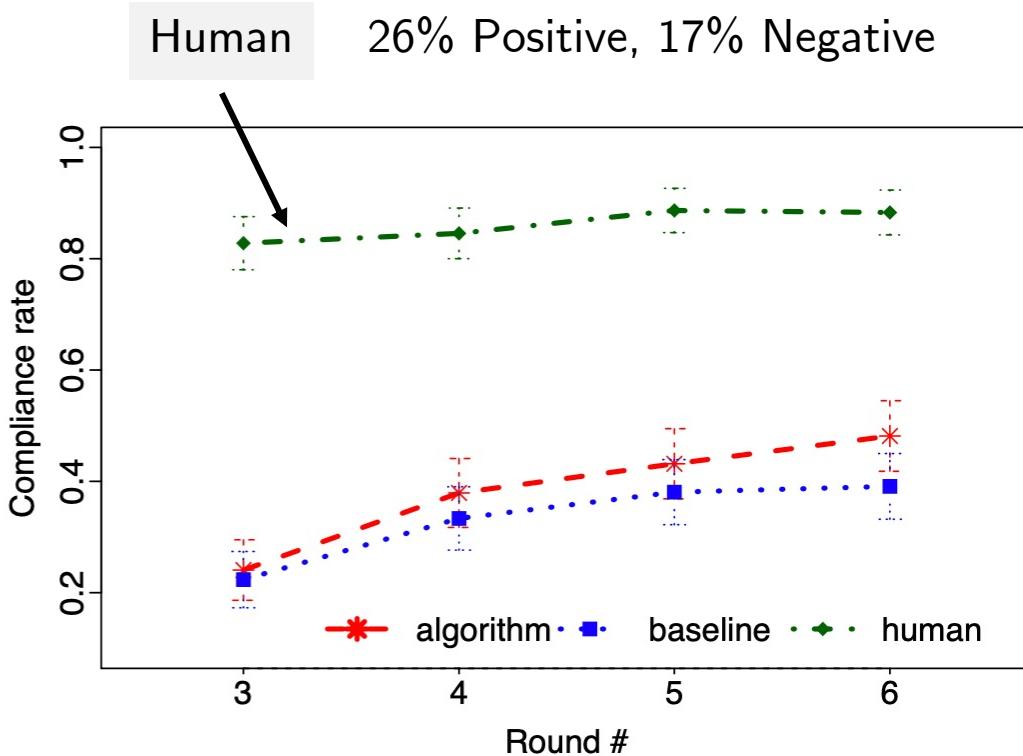
Complying with Intuitive Tip



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

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**."

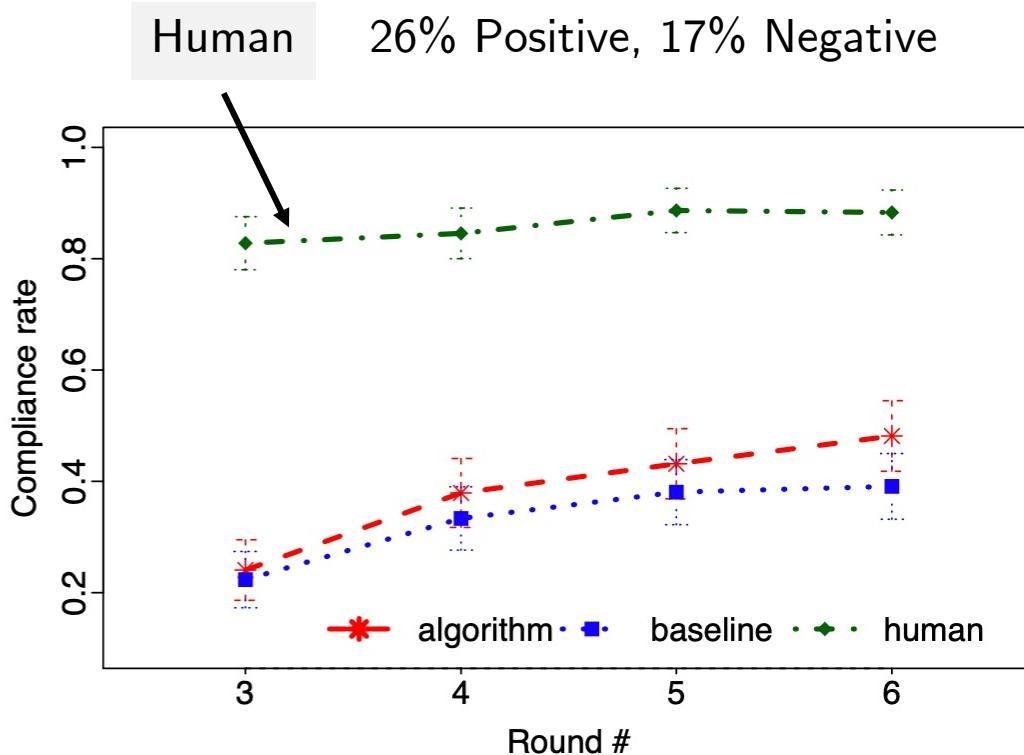
R_d6YSuigdikyaNdT

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

R_1pA8wDYgWc9hbIt

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

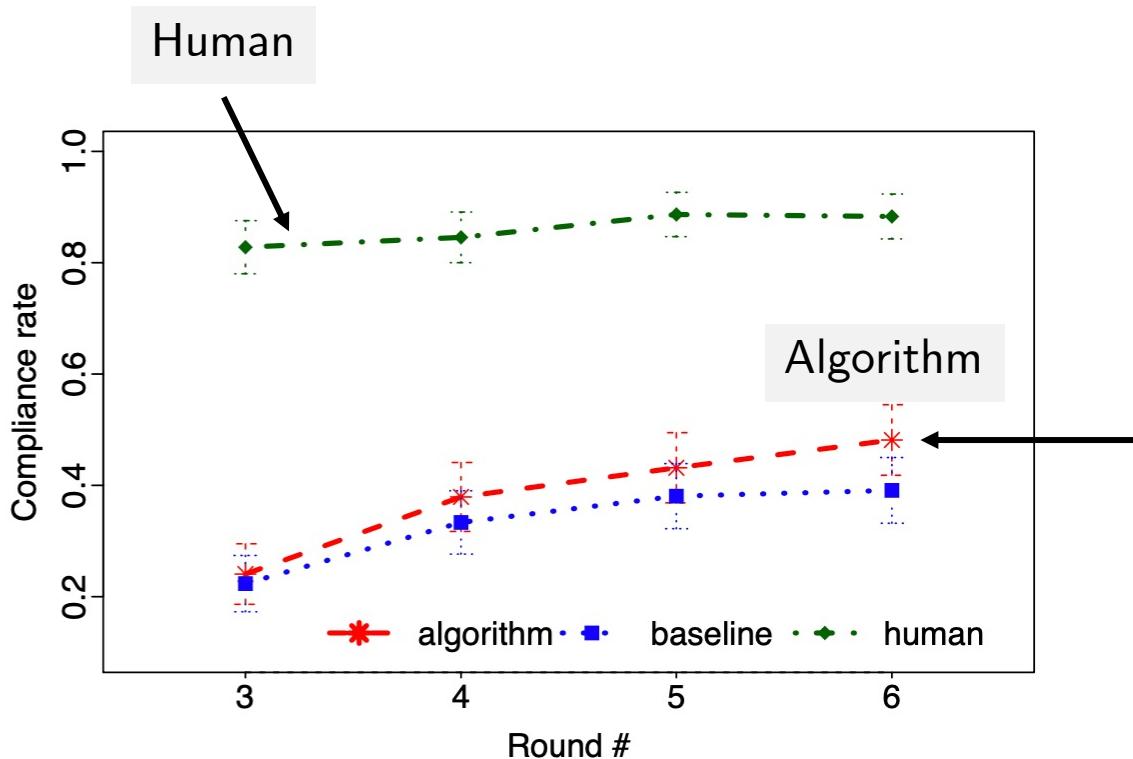
"It stunk honestly. **The server takes forever to cook**."

R_beijQ8guDyExa5r

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

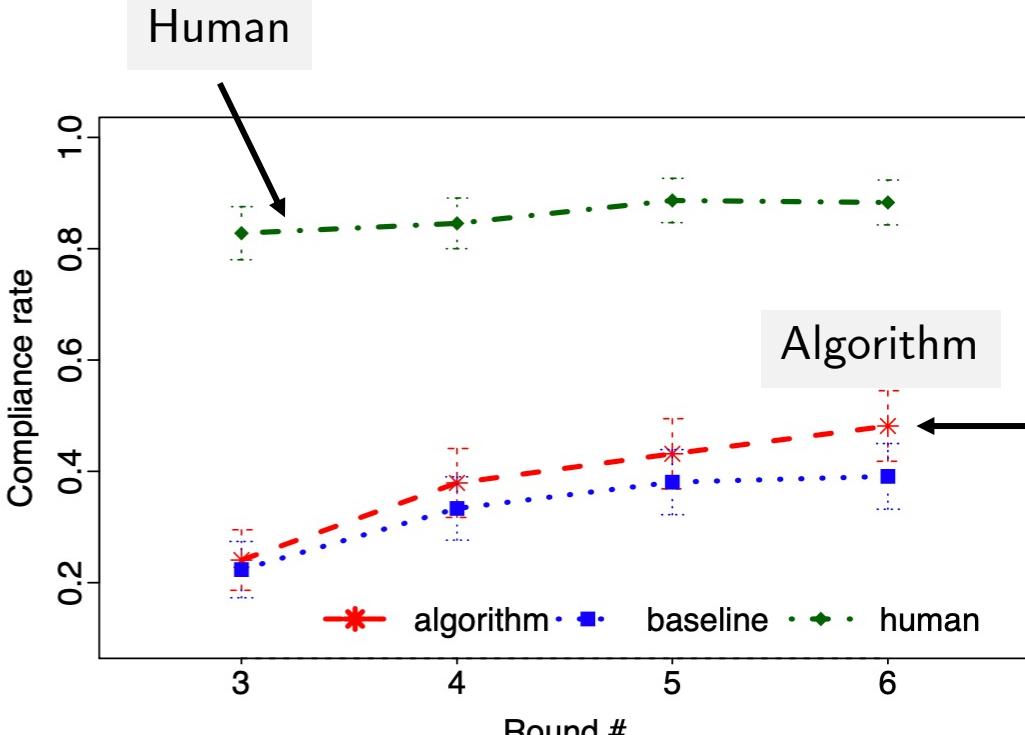
Results

Against Counterintuitive Tips



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

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

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

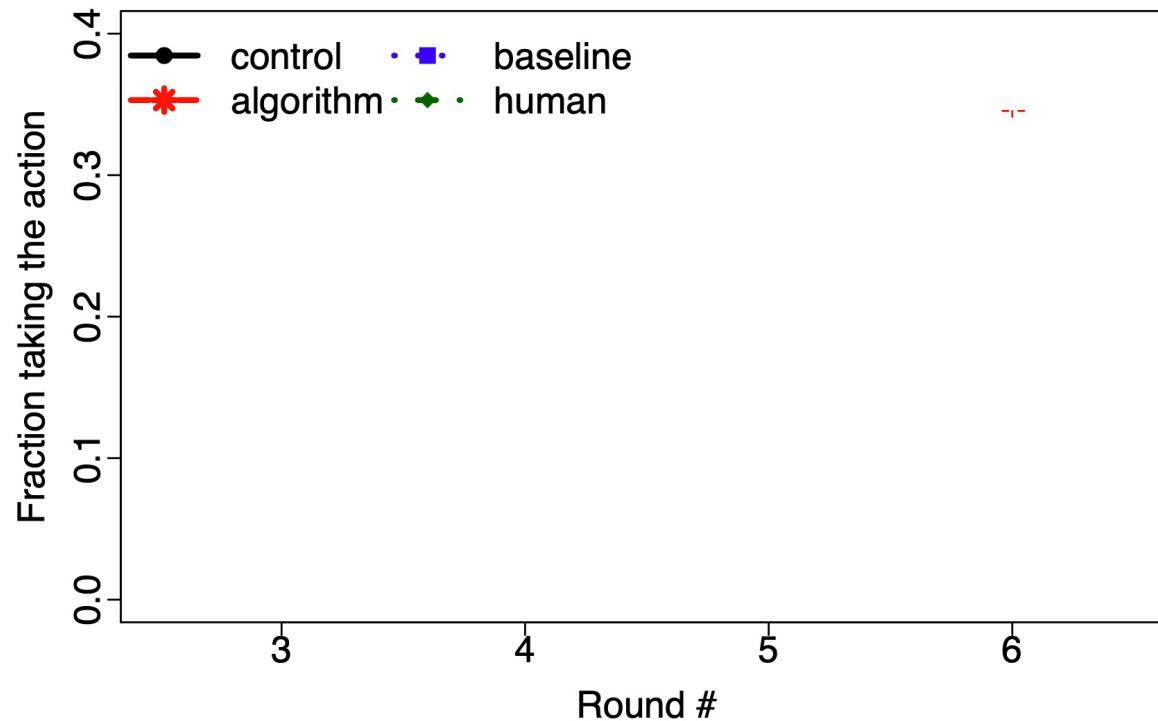
	Chop	Cook	Plate	
Sous-Chef	3	2	2	times
Server	1	2	2	times

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 shows values 3, 2, and 2 respectively. The Server row shows values 1, 2, and 2 respectively. The word 'times' is placed to the right of each row, indicating the frequency of each action. Below the table, two arrows point upwards from the words 'Algorithm' and 'Baseline' to the sous-chef and server rows respectively.

Results Learning Beyond Tips

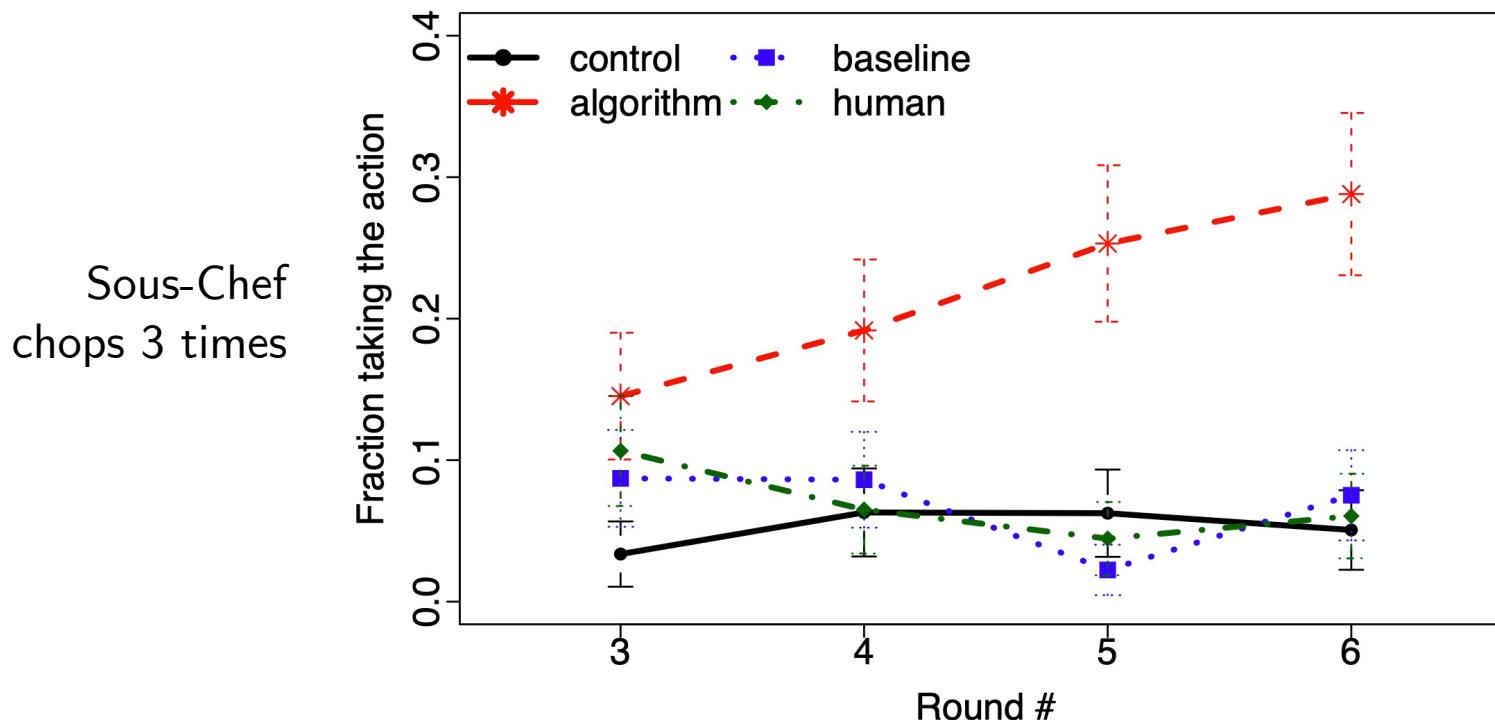
Sous-Chef
chops 3 times



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

Results Learning Beyond Tips

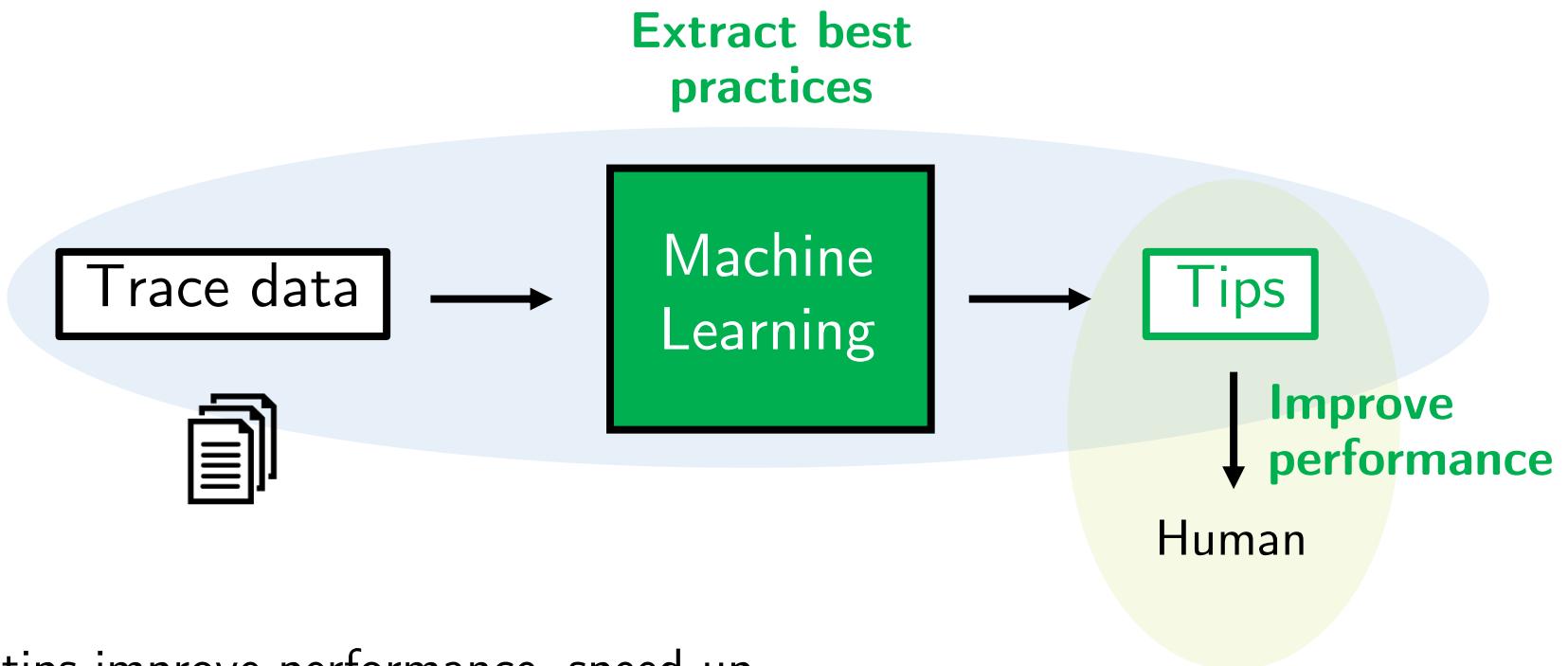
Our tip effectively led people to the states they can learn other optimal strategies



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

Summary

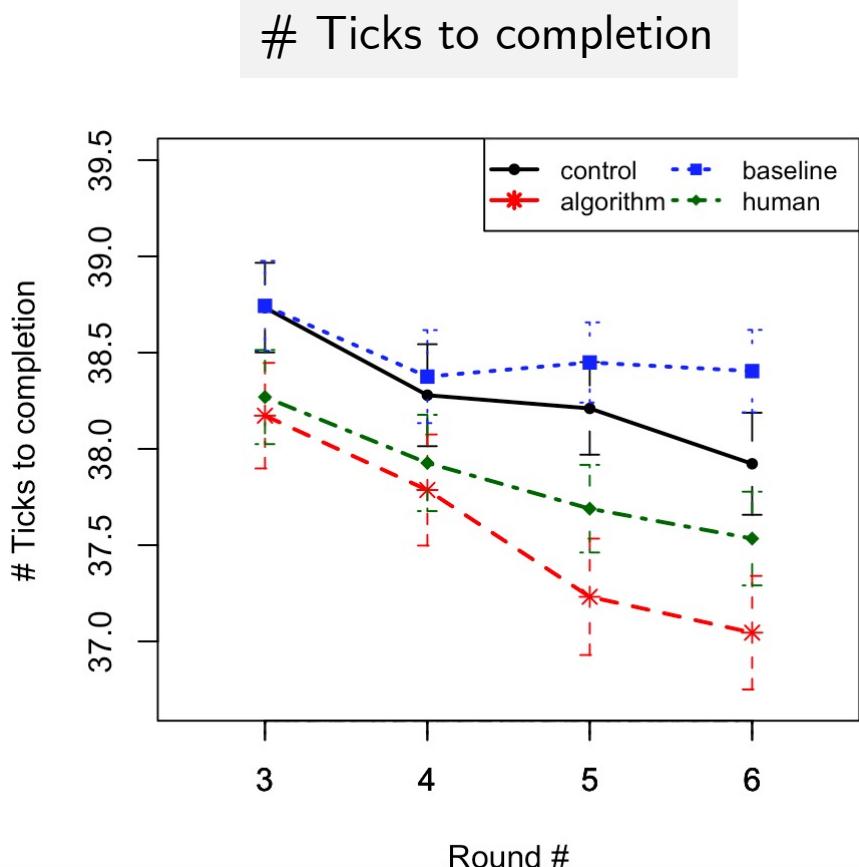
ML to automatically extract simple tips
that help people improve in a dynamic way



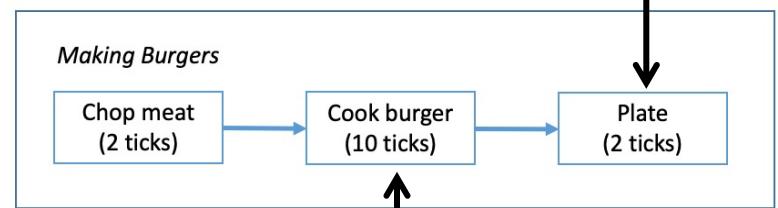
Our tips improve performance, speed up learning, help adapt to disruption, and uncover other optimal strategies

Feedback (tips) very welcome!

Results Good Tip = Consequential



Baseline Sous-Chef should plate twice



Algorithm Server should cook twice

Next Tick	Current Tick: 0/50	Orders Completed: 0
------------------	---------------------------	----------------------------

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
--	--	--	--------

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
------------------	---------------------------	----------------------------

Tip: Never assign plating to the Chef.

Orders

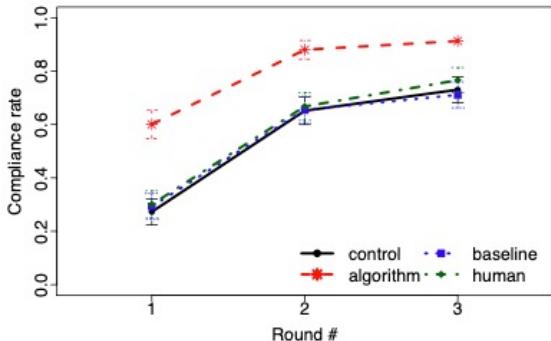
burger (0/3)	burger (0/3)	burger (0/3)	burger
--------------	--------------	--------------	--------

Workers

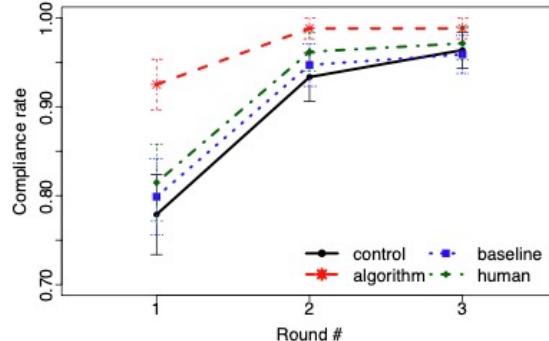
chef	sous-chef	server

(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.

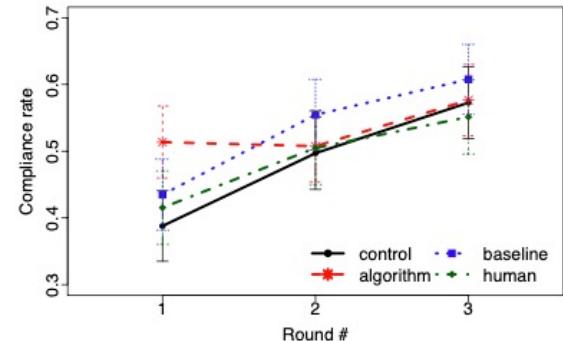
Learning Beyond Tips



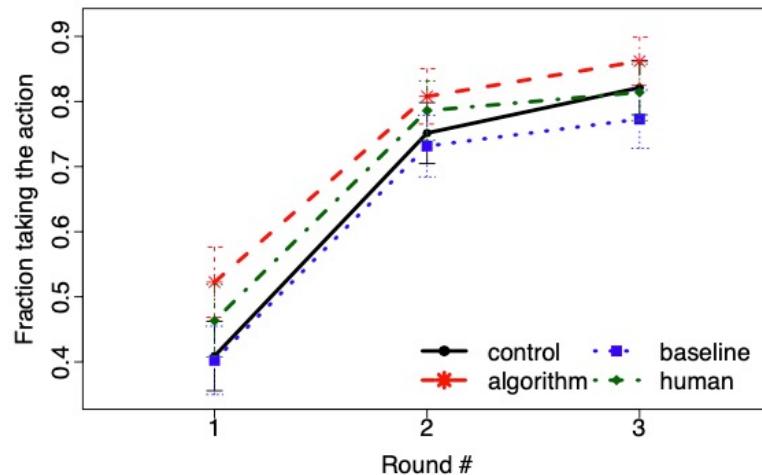
(a) Algorithm: “Chef shouldn’t plate”



(b) Human: “Leave some idle”



(c) Baseline: “Chef chops once”

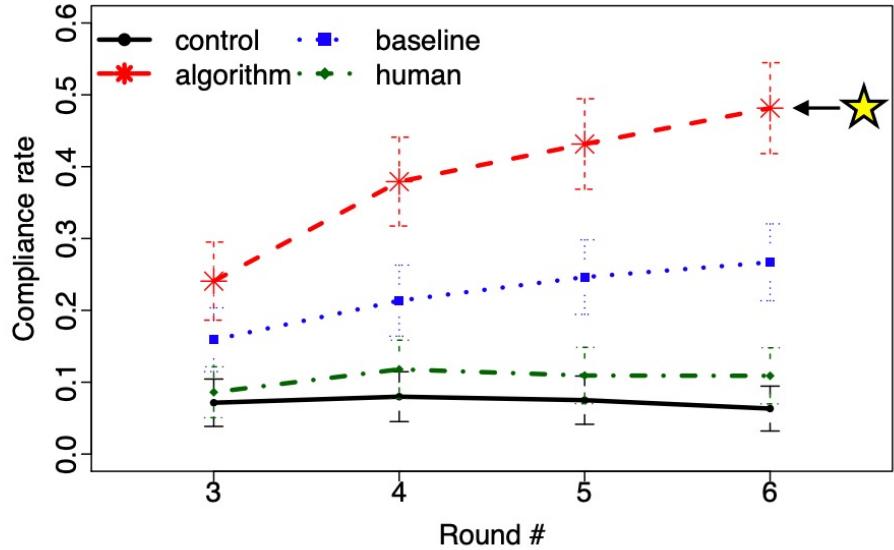


(a) Fully-staffed: “Server shouldn’t cook”

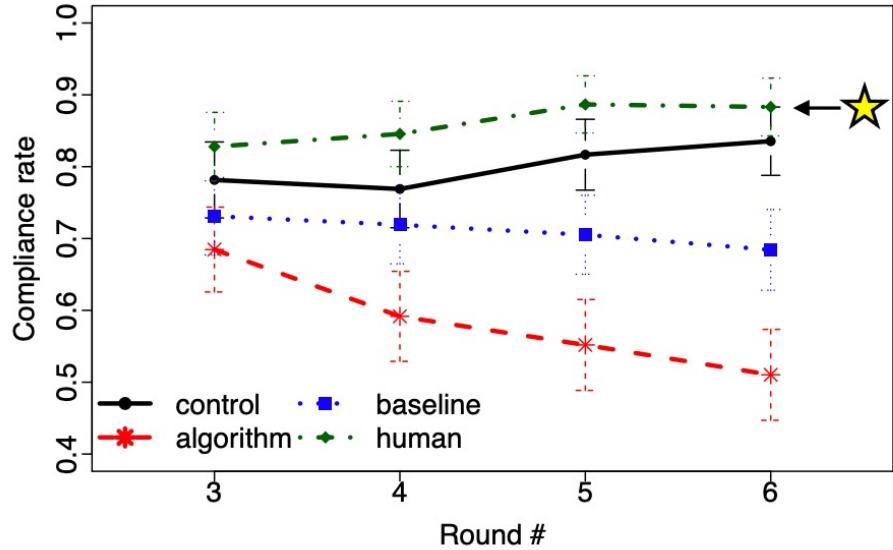
Optimal Policies

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.

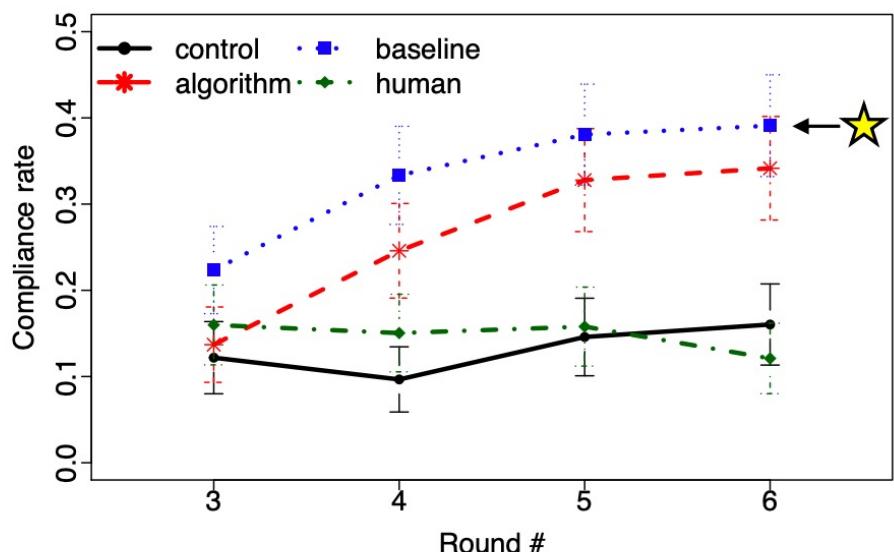
Understaffed scenario: In this scenario, the participant has access to only two virtual workers—namely, the sous-chef and the server. The optimal number of steps needed to complete this scenario is 34 ticks. The keys insights to achieving the optimal performance are: (i) both workers should be assigned 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.



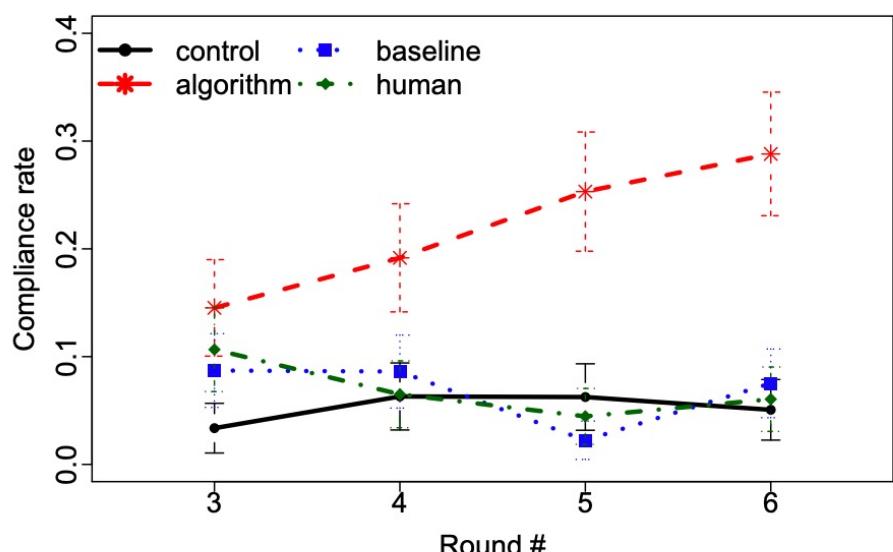
(a) Algorithm Tip: “Server cooks twice”



(b) Human Tip: “Server cooks once”



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



(d) Unshown Tip: “Server chops once”

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).