Improving Human Decision-Making
with Machine Learning

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Learning is Costly

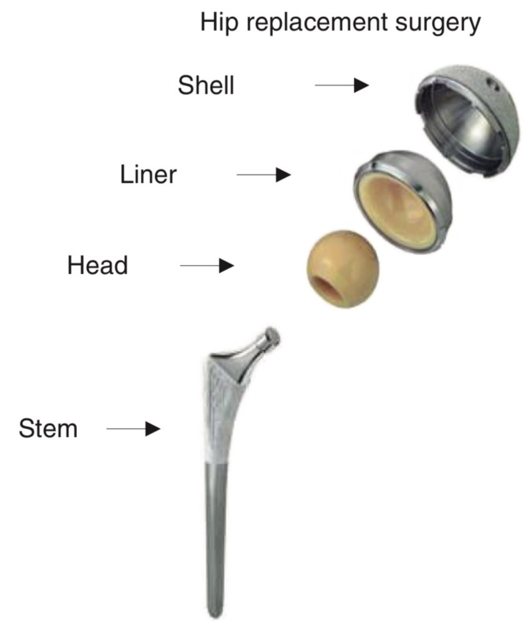
2+ years

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

+10.9%

productivity

- Song et al. 2018

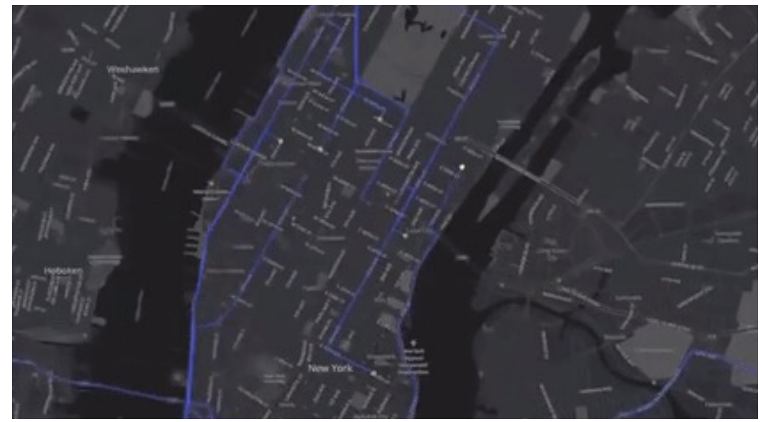
Also – Chan et al 2014, Herkenhoff et al 2018, Tan & Netessine 2019, Jarosch et al 2019, ...

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

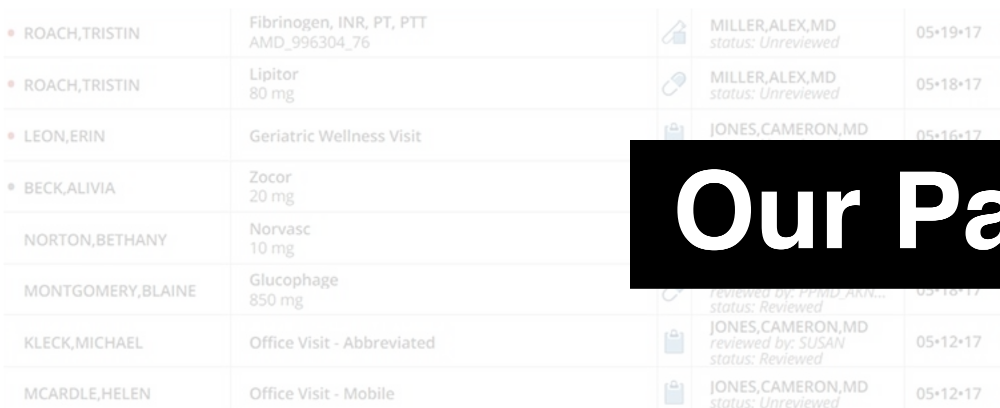
Noisy, high-volume data
hard to extract insights

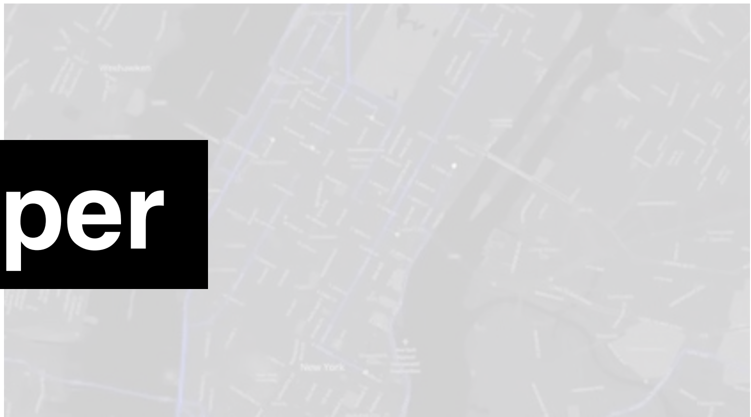
Key Q: can insights from ML
improve human decision-making?

Trace Data is Everywhere

Physicians

Uber Drivers





Our Paper

Extract best practices

Mine simple tips

Trace data → Machine Learning → Tips

improve performance

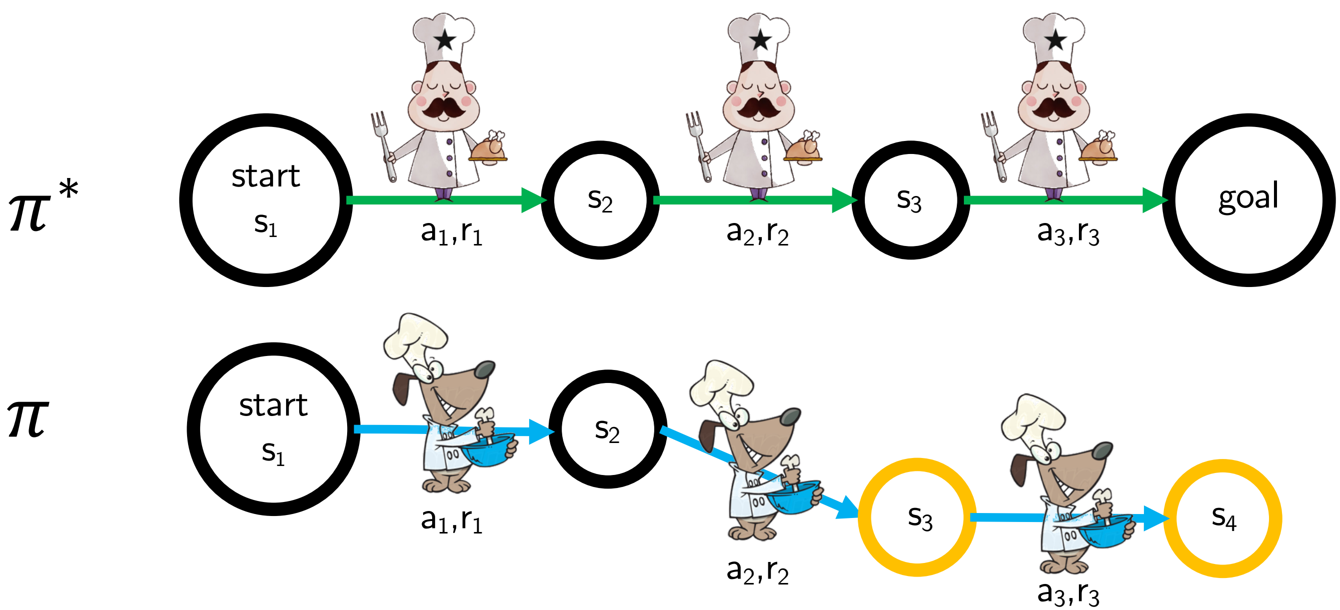
Human workers

Problem Formulation

MDP Formulation:

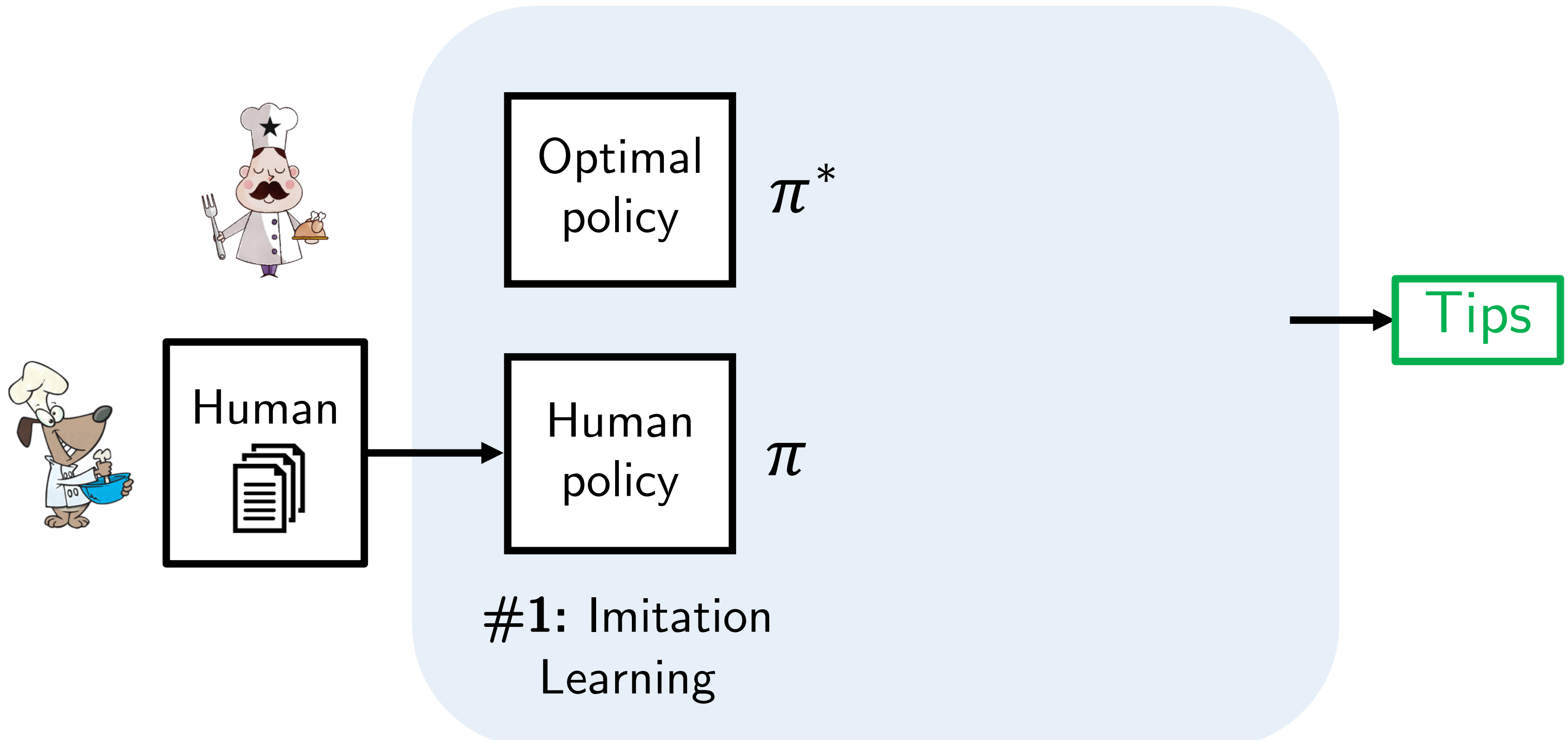
Optimal policy and *human* make sequences of decisions

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



Our Approach

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



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

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

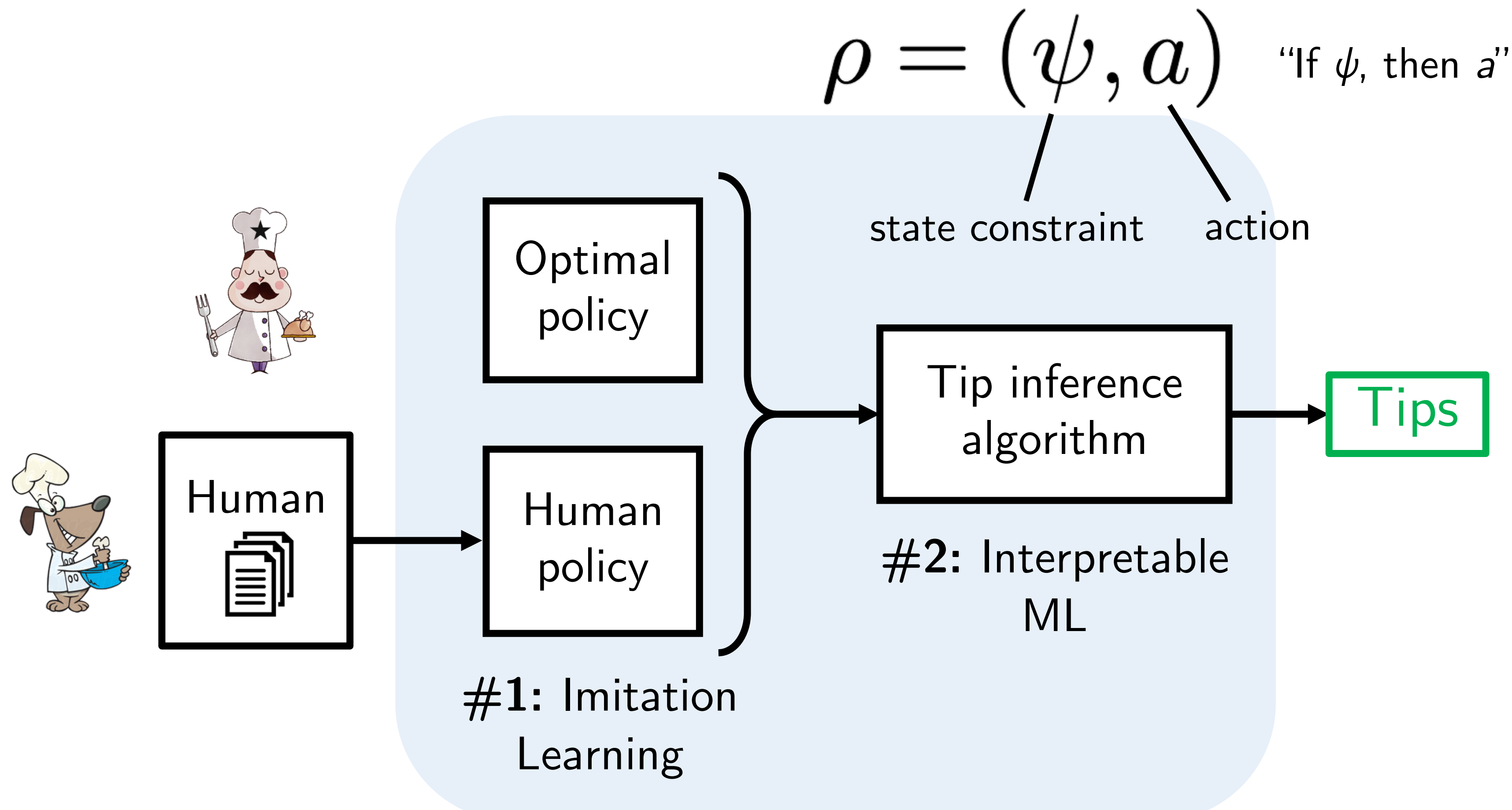
Parametrize policy using DNN π_θ

Optimize θ using the policy gradient algorithm

- Williams 1992, Sutton 2000

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

Our Approach



Caruana et al. 2015, Letham et al. 2015

Step 2: Interpretable RL

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

$$J(\rho) = \underbrace{V^{\pi_\mathrm{h} \oplus \rho}(s_0)}_{\text{Human policy + tip}} - \underbrace{V^{\pi_\mathrm{h}}(s_0)}_{\text{Only human policy}}$$

  - $\pi_\mathrm{h} \oplus \rho$ denotes overriding the human policy with tip ρ.
  - $V^{\pi}(s)$ is the value function and s_0 is the initial state.
  - J measures the improvement in human reward

- **Intuition:** Want tips that maximize performance
  - Assumes the human follows the tip exactly

- **Challenge:** Hard to estimate $V^{\pi_\mathrm{h} \oplus \rho}$

Step 2: Interpretable RL

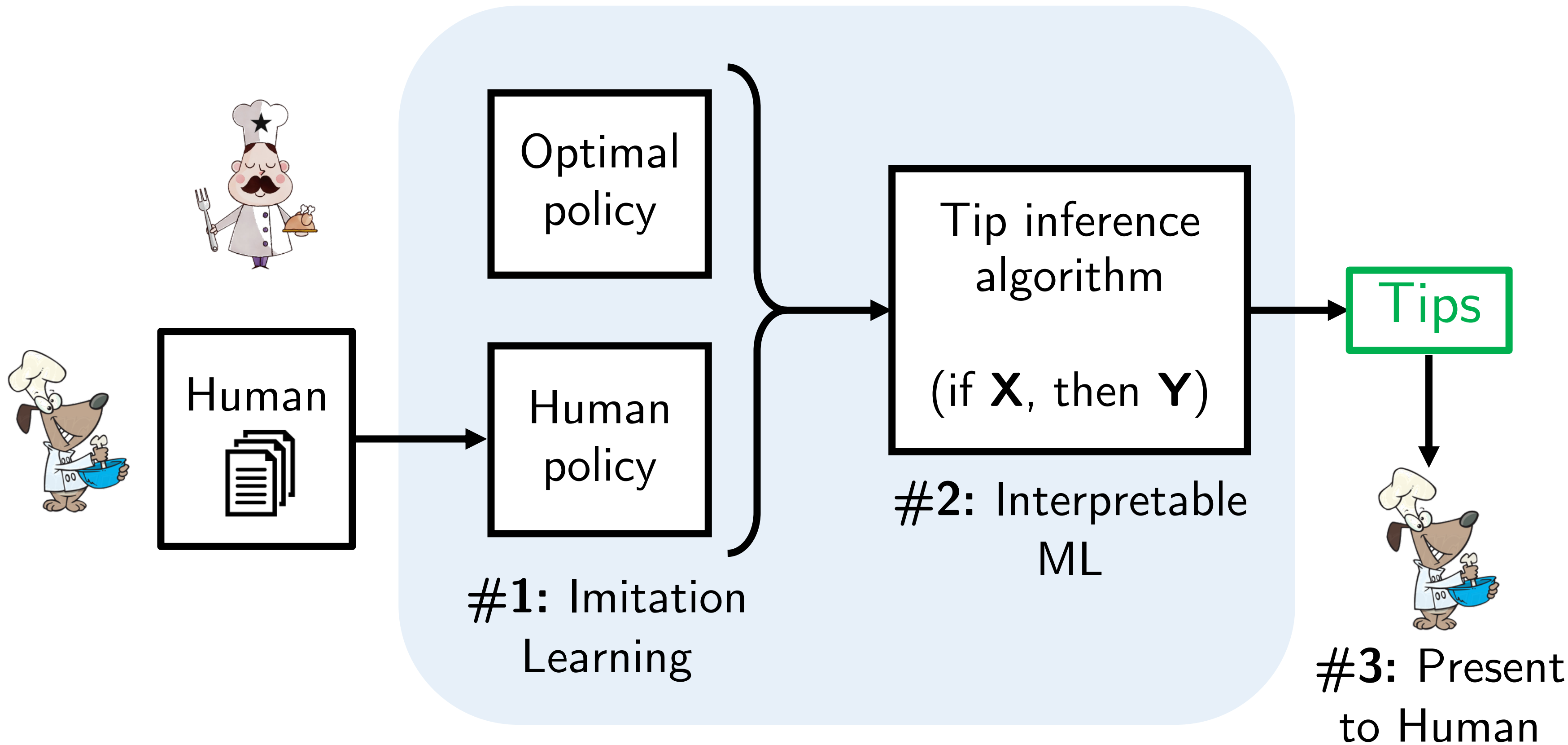
- **Key Lemma:** We have

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

  - 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

- Rank tips based on expected improvement

Our Approach



Queueing Game

Burger Queen

x 4 within 50 ticks

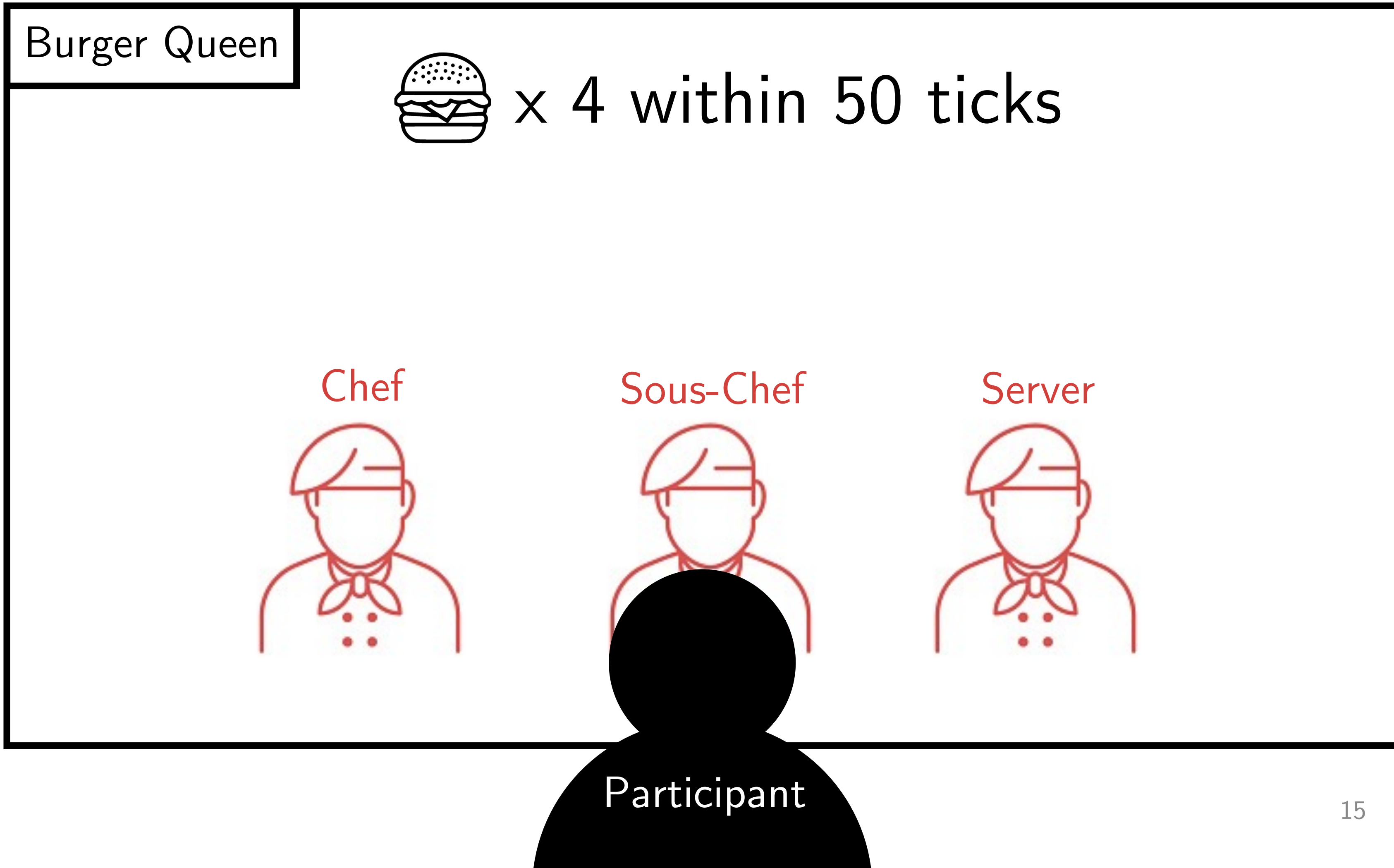
Making Burgers

Chop meat (2 ticks) → Cook burger (10 ticks) → Plate (2 ticks)

Participant

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

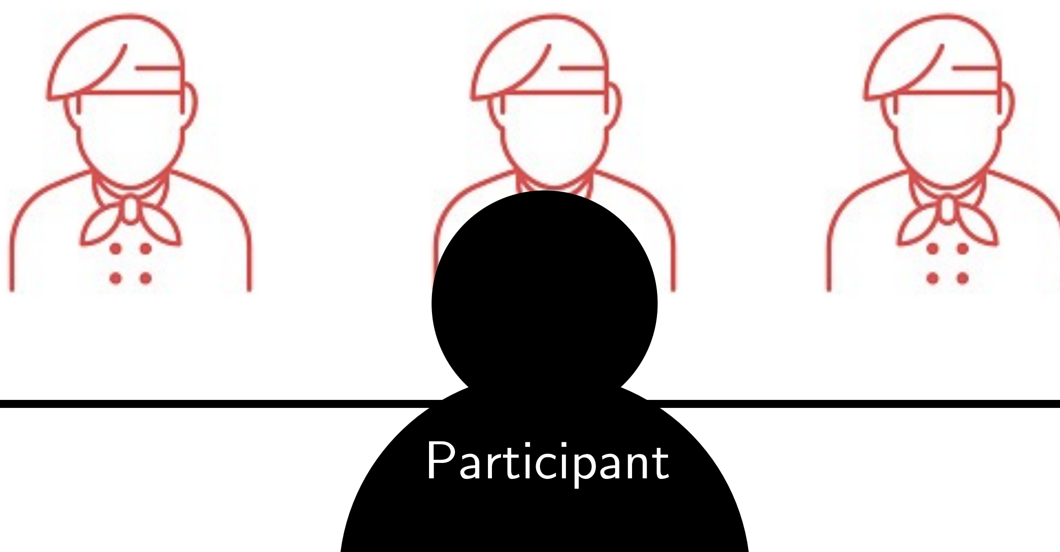
Queueing Game



Queueing Game

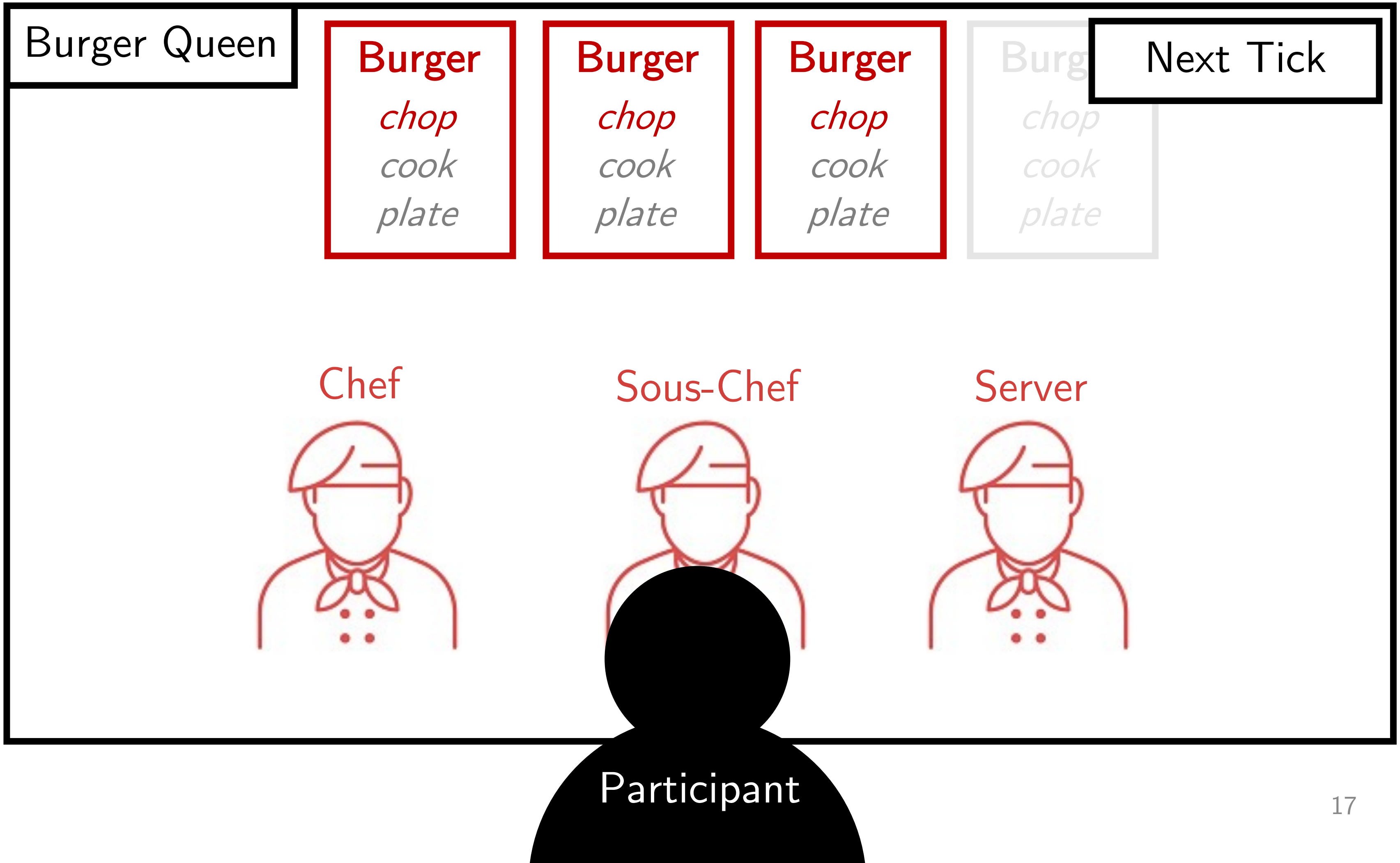
Burger Queen

Chopping:	Fast	Average	Slow
Cooking:	Fast	Average	Slow
Plating:	Slow	Average	Fast
	Chef	Sous-Chef	Server



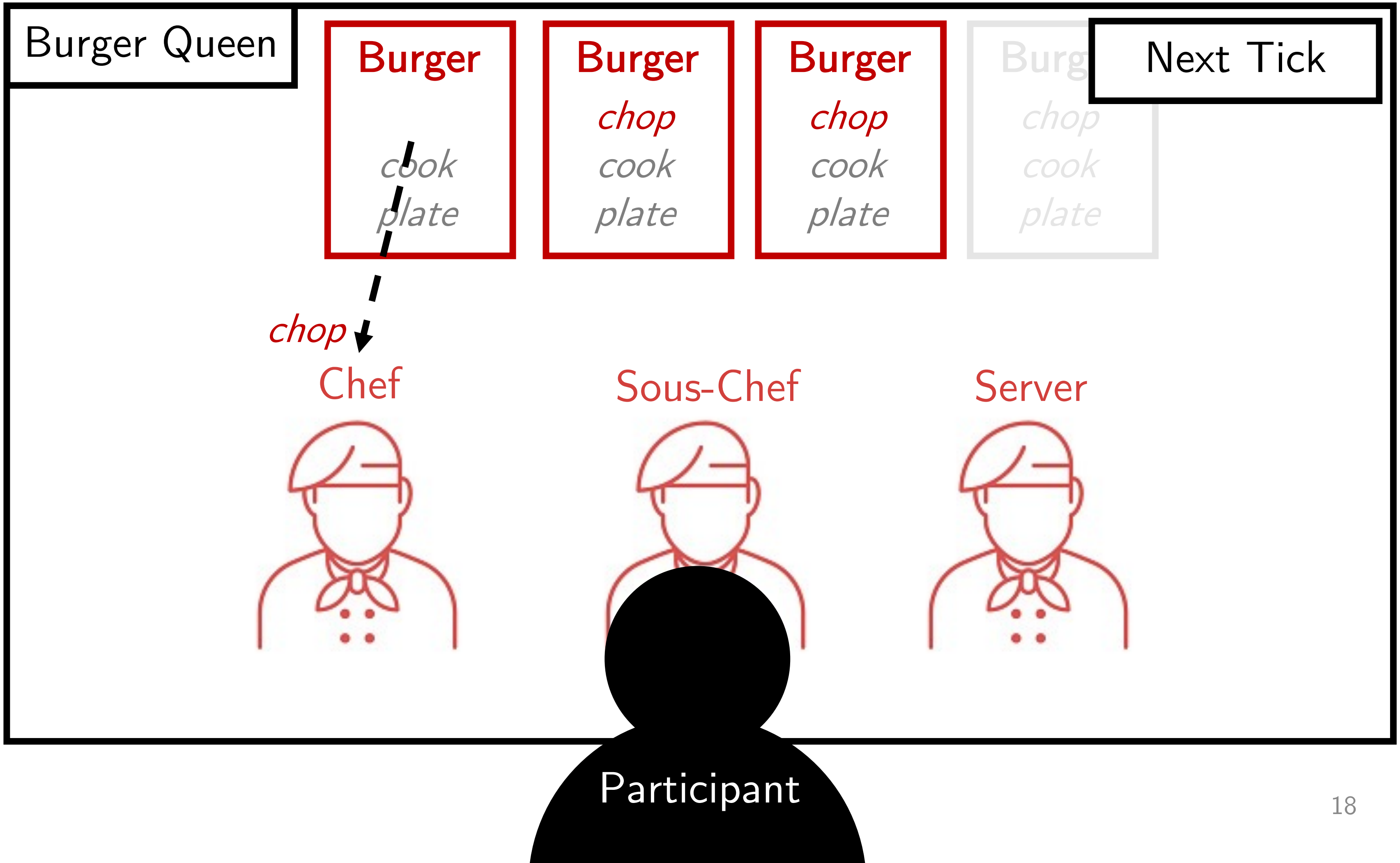
Queueing Game

Reward: 0
Tick #1/50



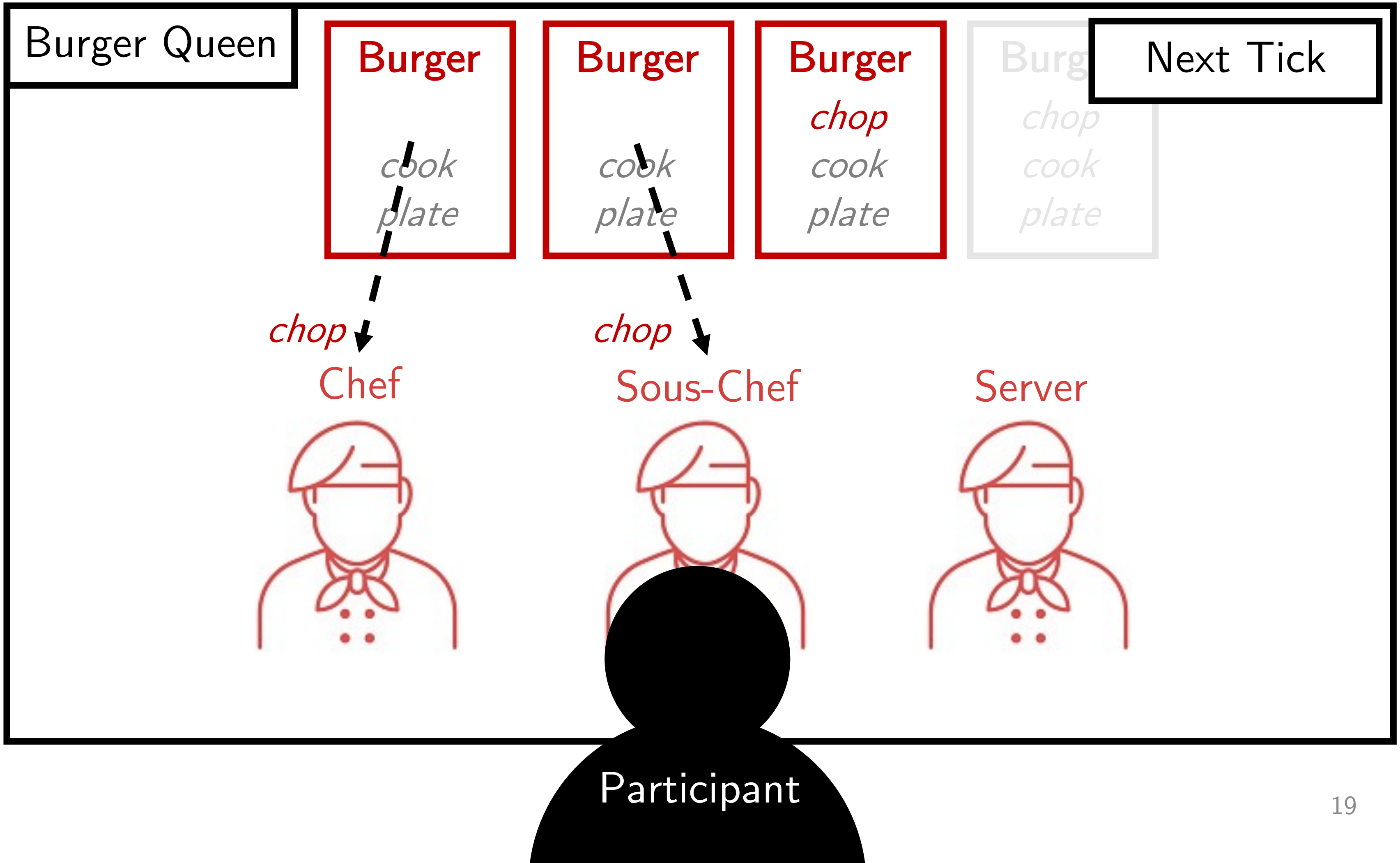
Queueing Game

Reward: 0
Tick #1/50

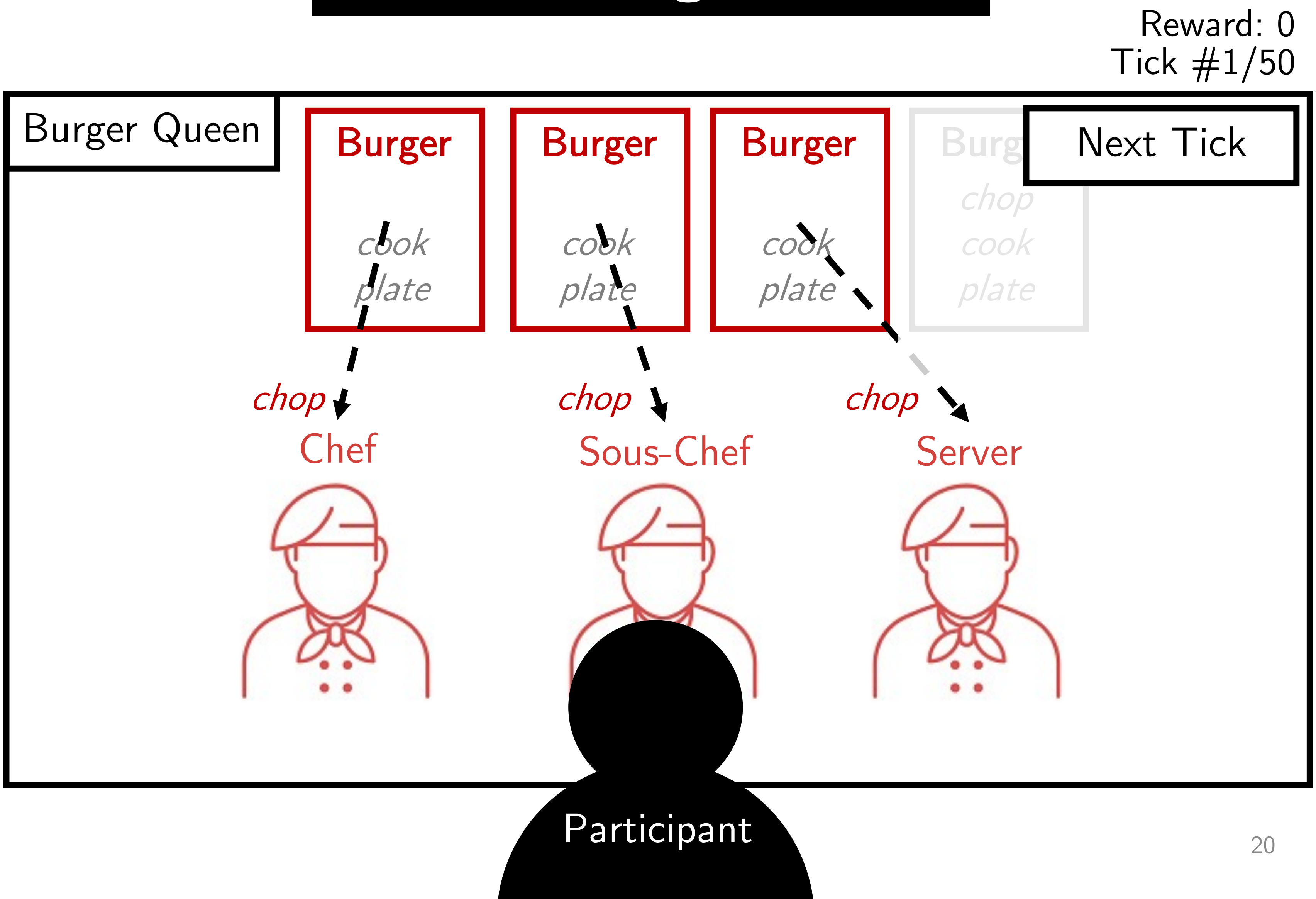


Queueing Game

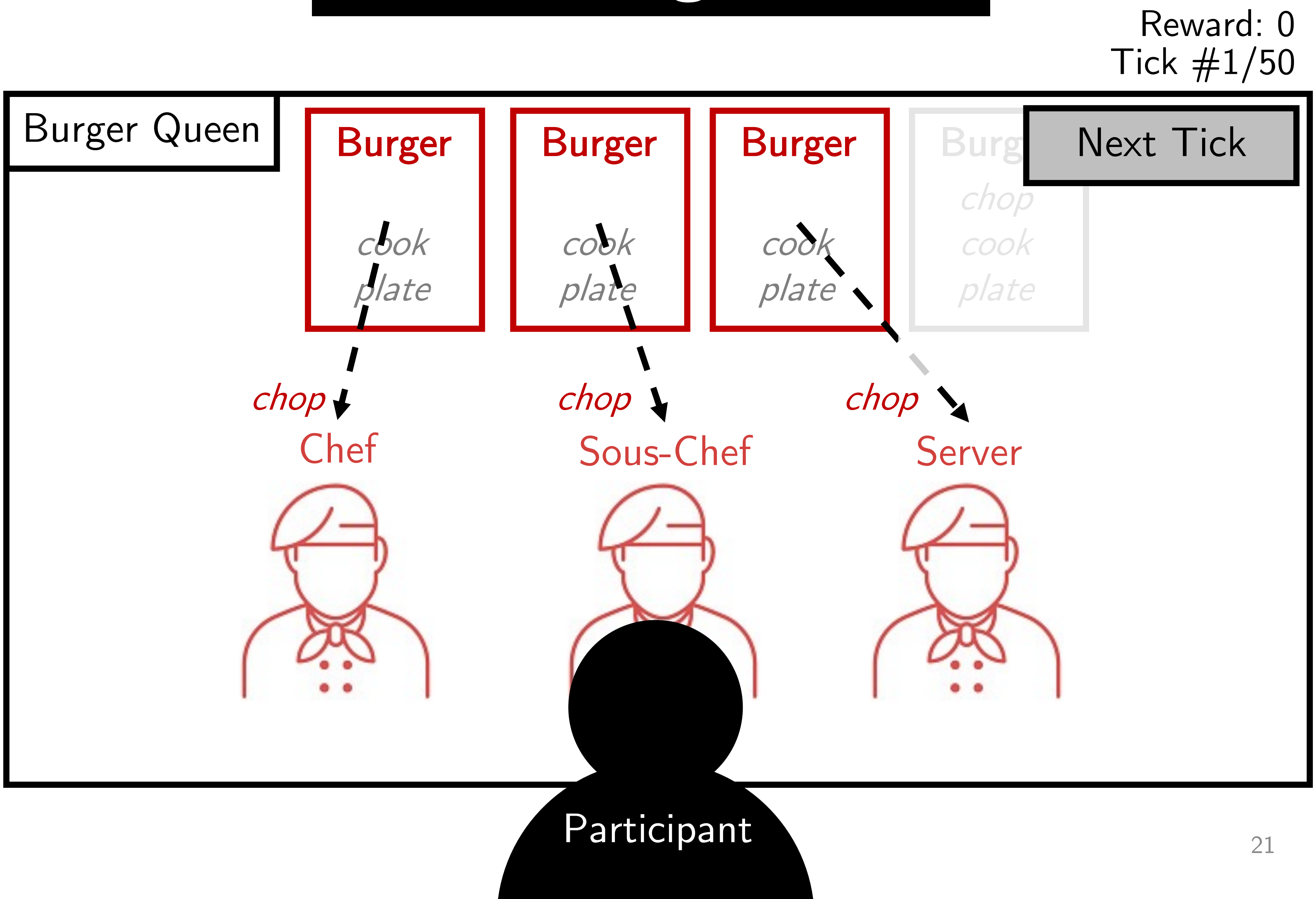
Reward: 0
Tick #1/50



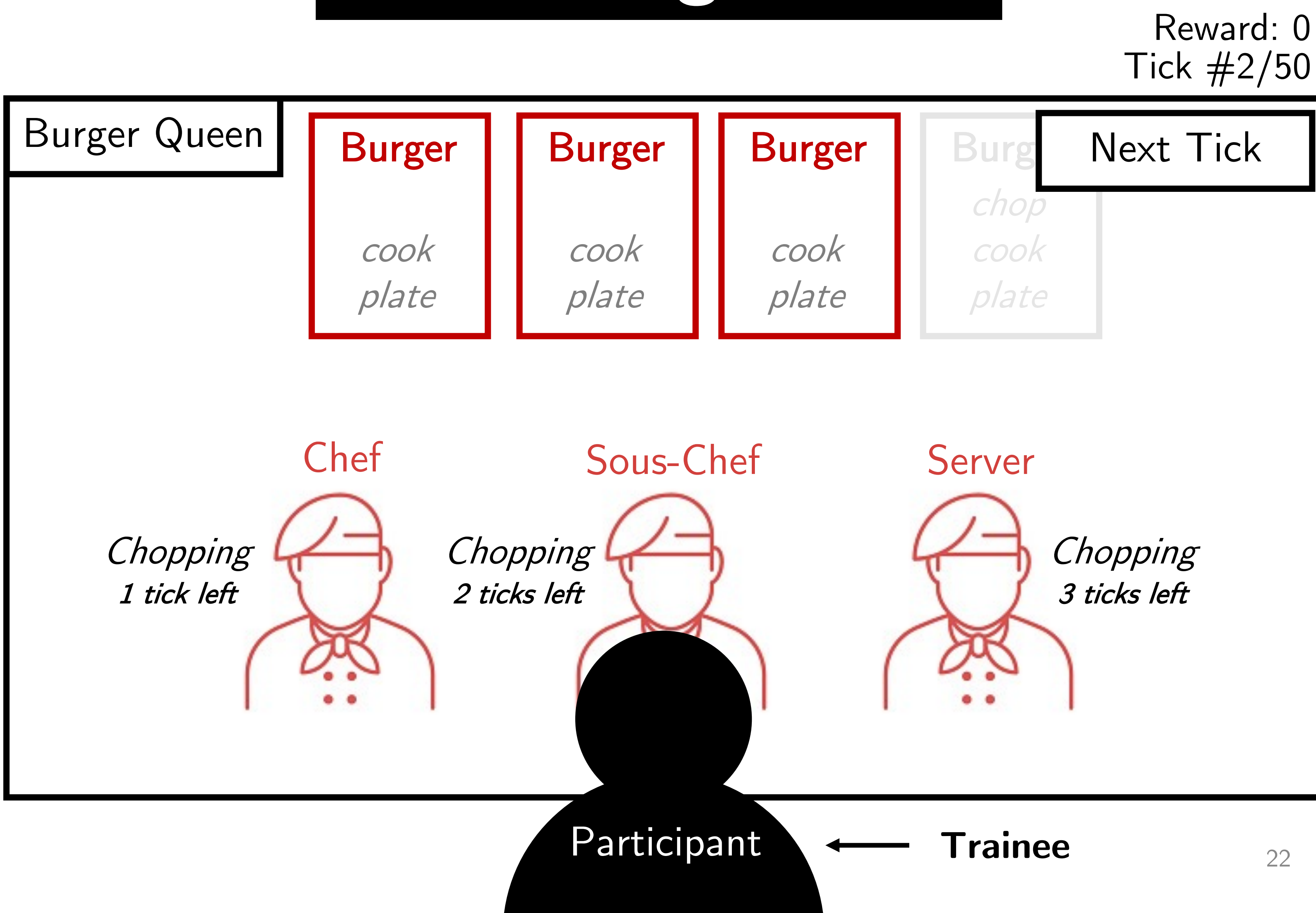
Queueing Game



Queueing Game



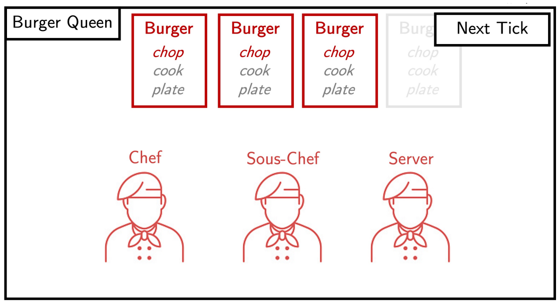
Queueing Game



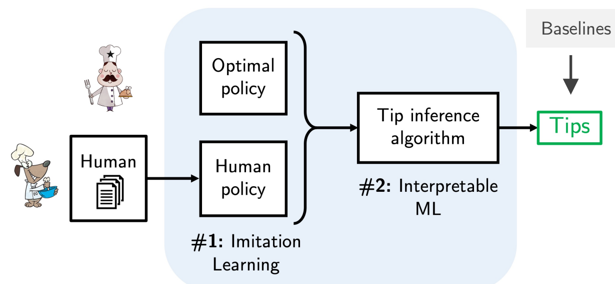
User Study Design

Phase I

N = 200



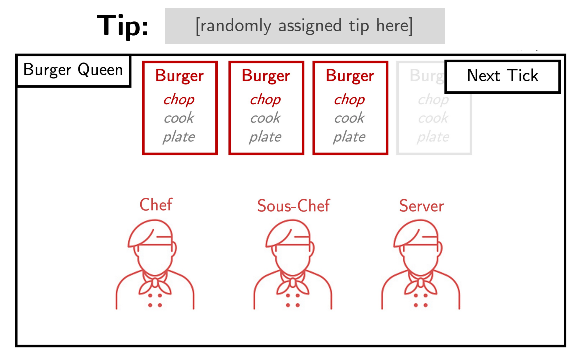
Gather trace data



Tip inference

N = 1400

Phase II



Tip evaluation

Environment

Normal

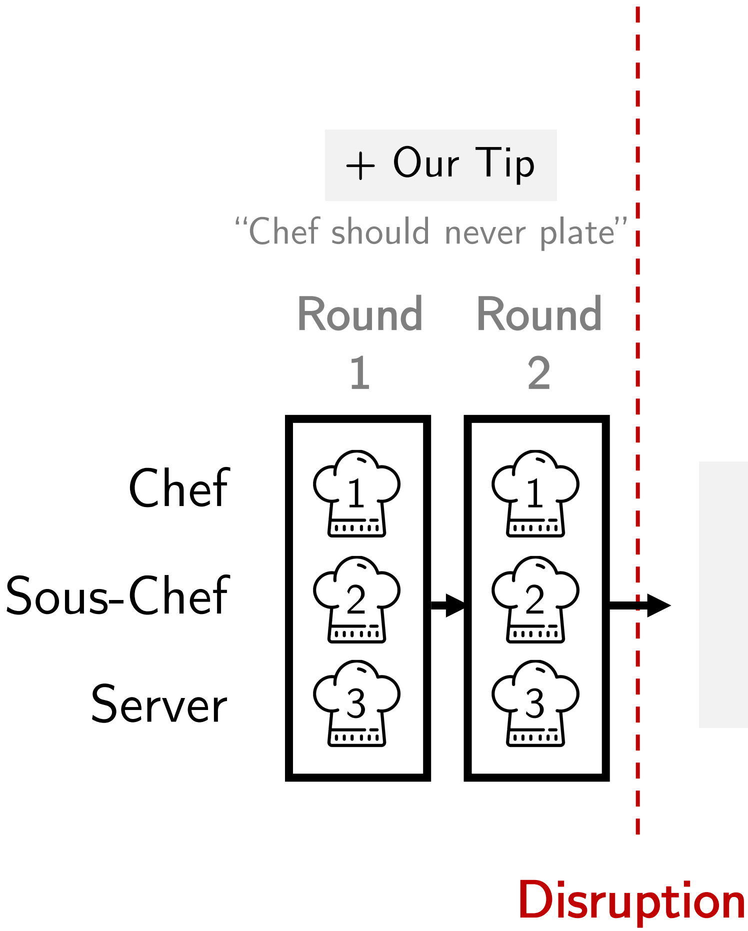
Disrupted

in the middle

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

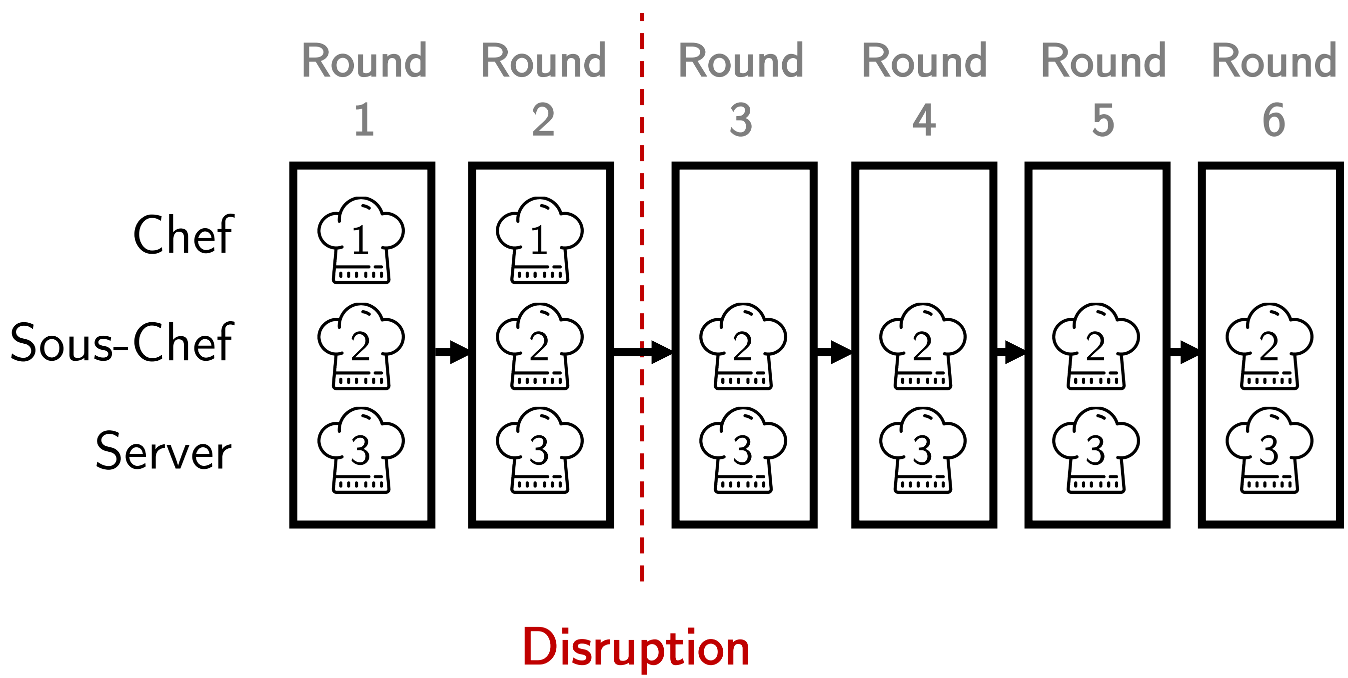
Design Disrupted Configuration

x 4 within 50 ticks



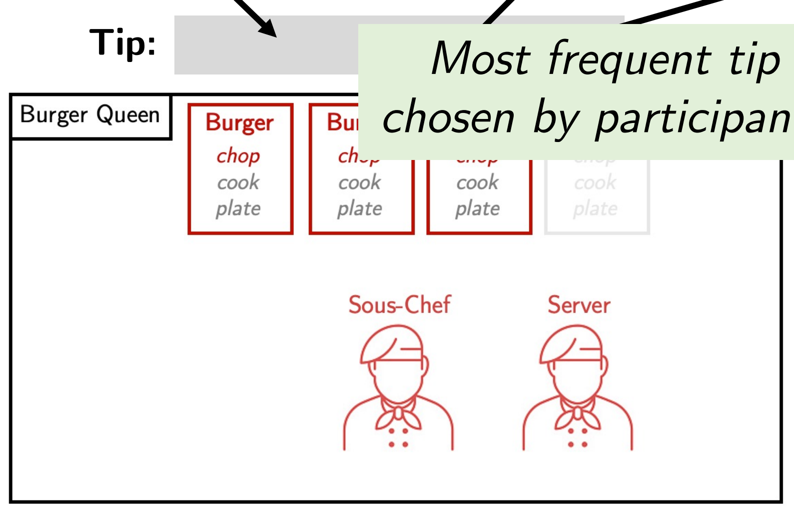
Unfortunately, the Chef is on vacation during this round.
(Who travels these days...)

Chopping:	Fast	Average	Slow
Cooking:	Fast	Average	Slow
Plating:	Slow	Average	Fast
	Chef	Sous-Chef	Server



Phase I Inferred Tips

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



Most frequent tip chosen by participants

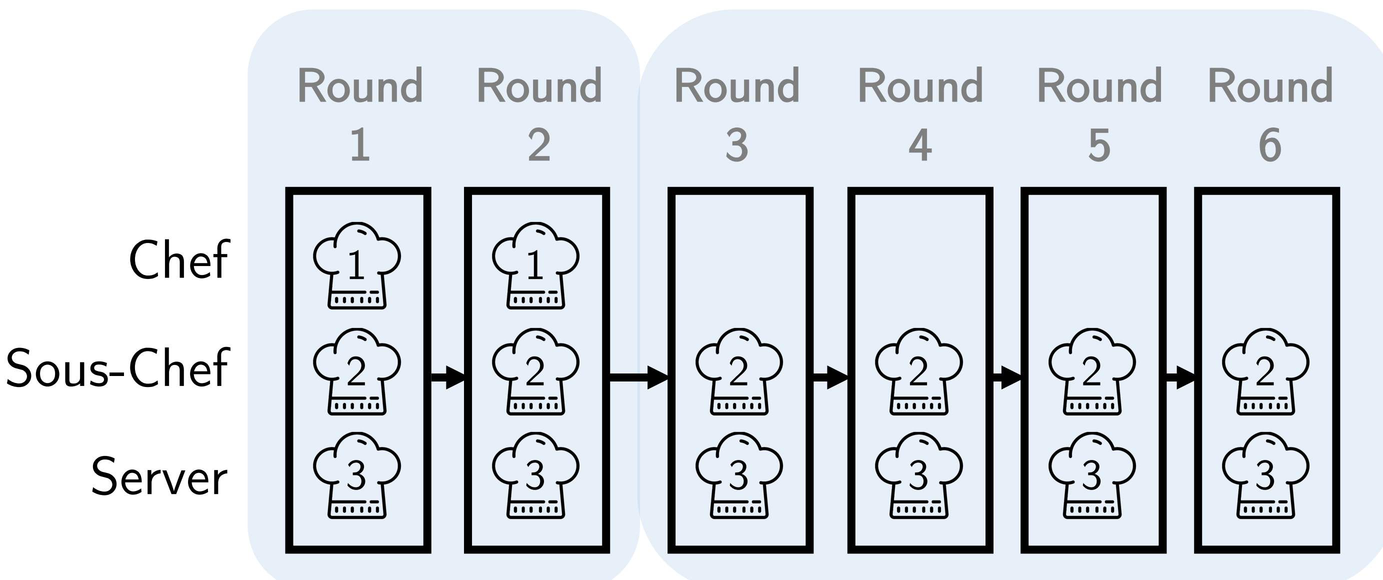
Most frequent s-a deviation b/w optimal and trainee policies

Amazon Mechanical Turk, N = 172

mean age 36.4, 62% female

Algorithm vs Human

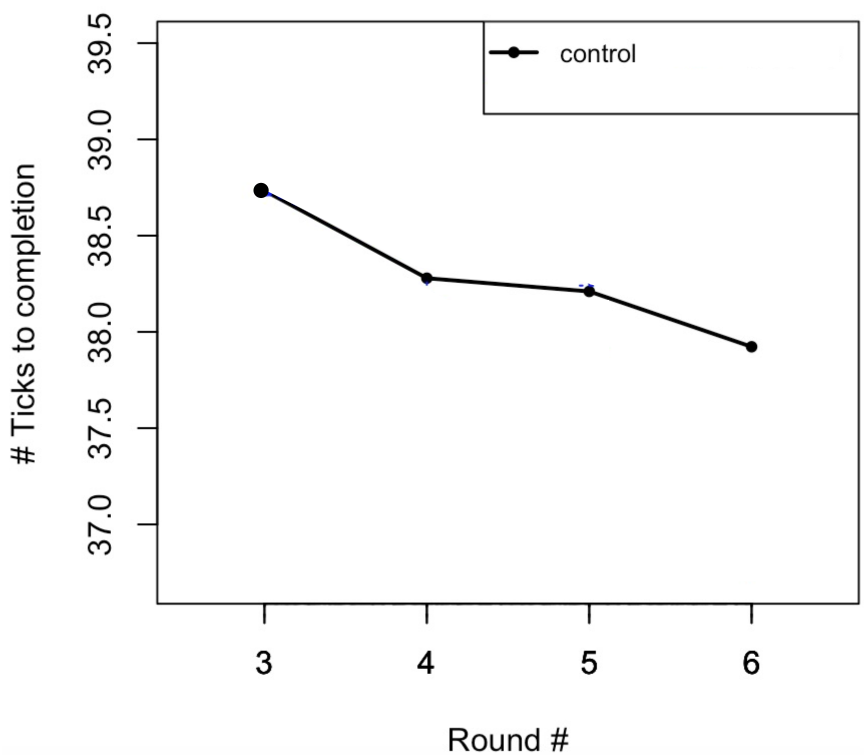
Algorithm	Human
Server should cook twice	Server should cook once



"Server shouldn't cook"

Results People Improve Over Time

Ticks to completion

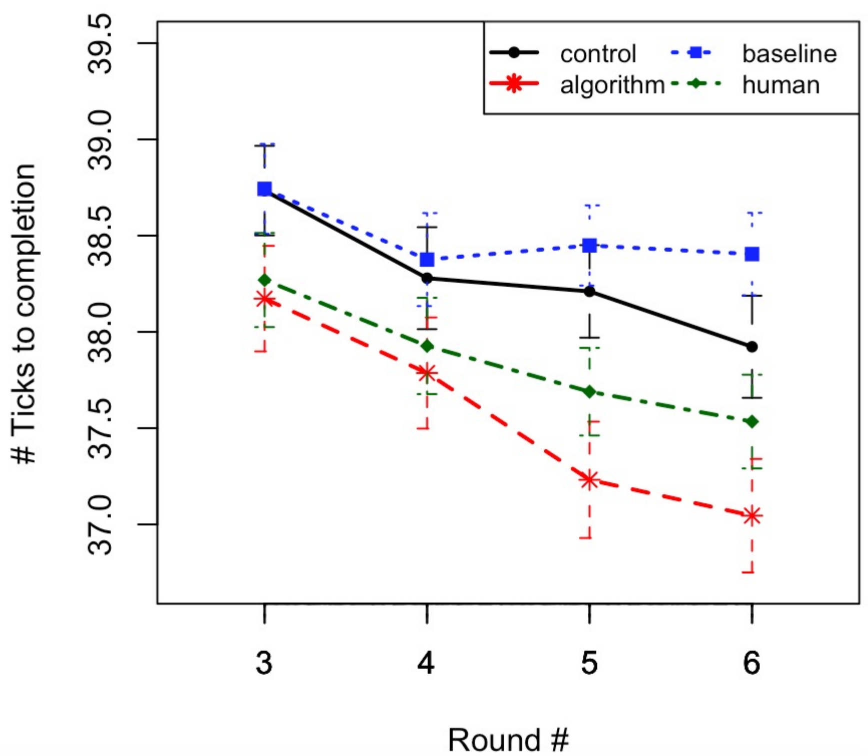


Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Results Our Tip Improves Performance

Ticks to completion



One-sided T-Tests

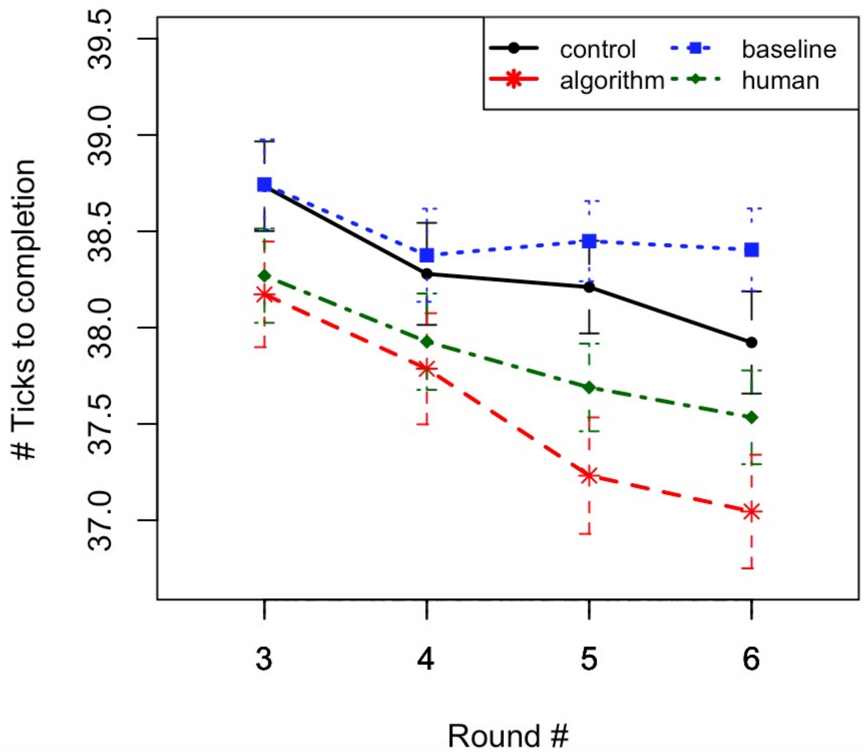
Algorithm *beats* Control ($p = 0.000008$)
Algorithm *beats* Human ($p = 0.006$)
Algorithm *beats* Baseline ($p <$ 1e-12)

Amazon Mechanical Turk, N = 1,011

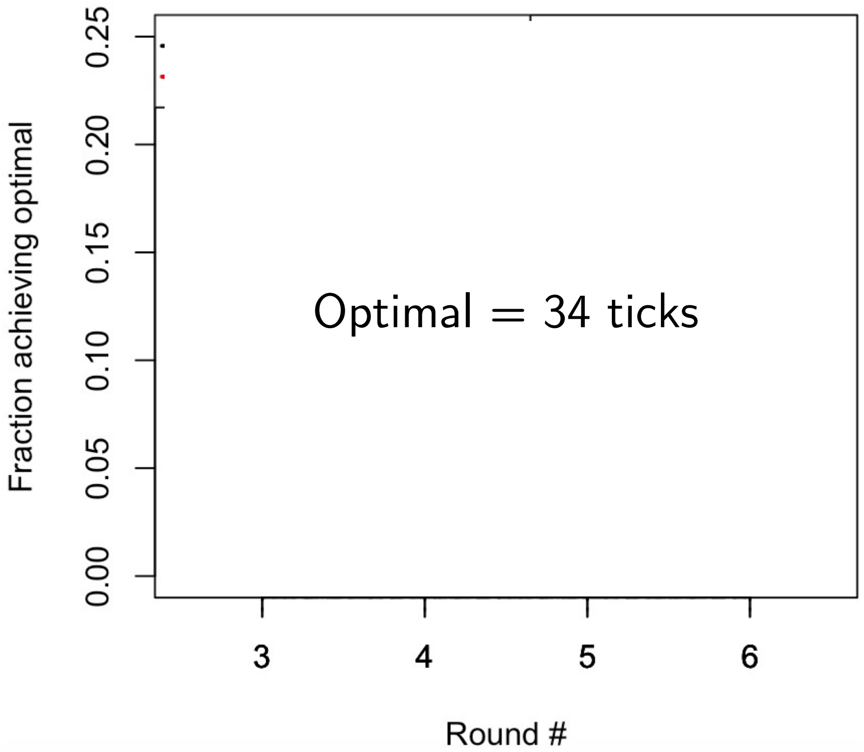
mean age 34.9, 60% female

Results

Ticks to completion



Fraction achieving optimal

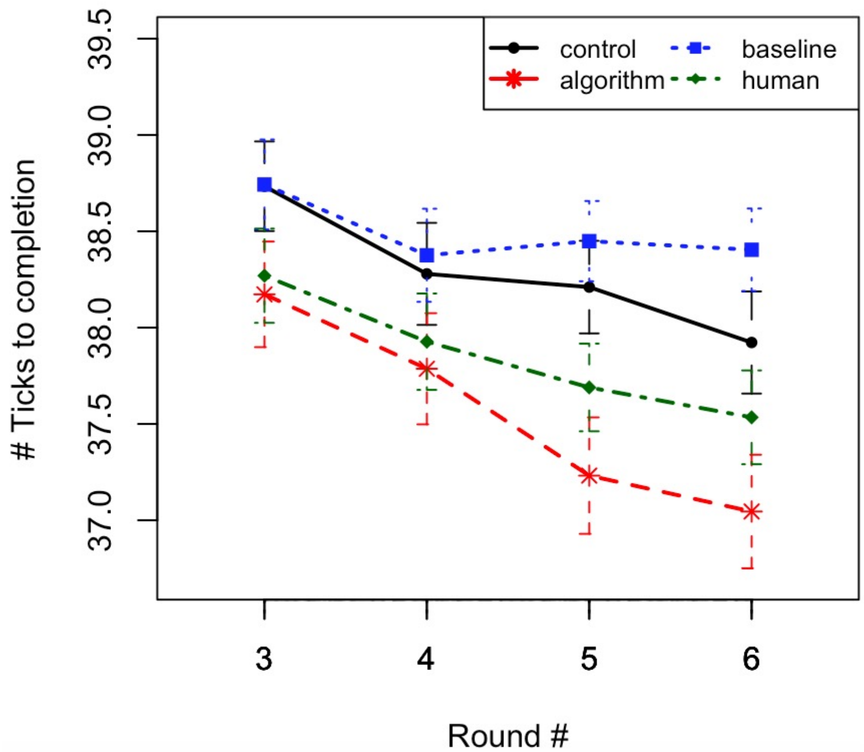


Amazon Mechanical Turk, N = 1,011

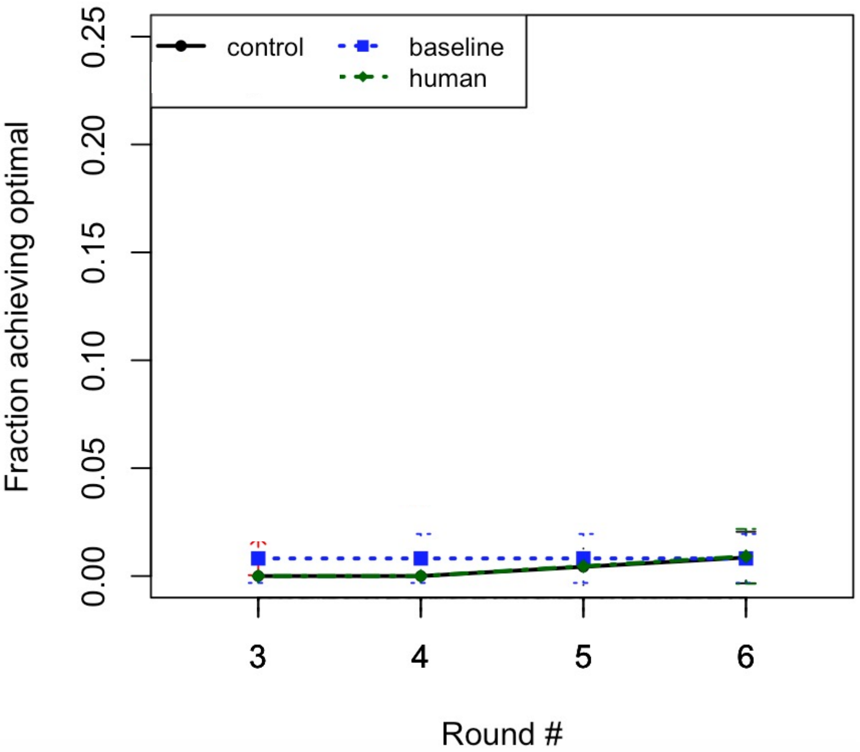
mean age 34.9, 60% female

Results Difficult to Reach Optimal

Ticks to completion



Fraction achieving optimal

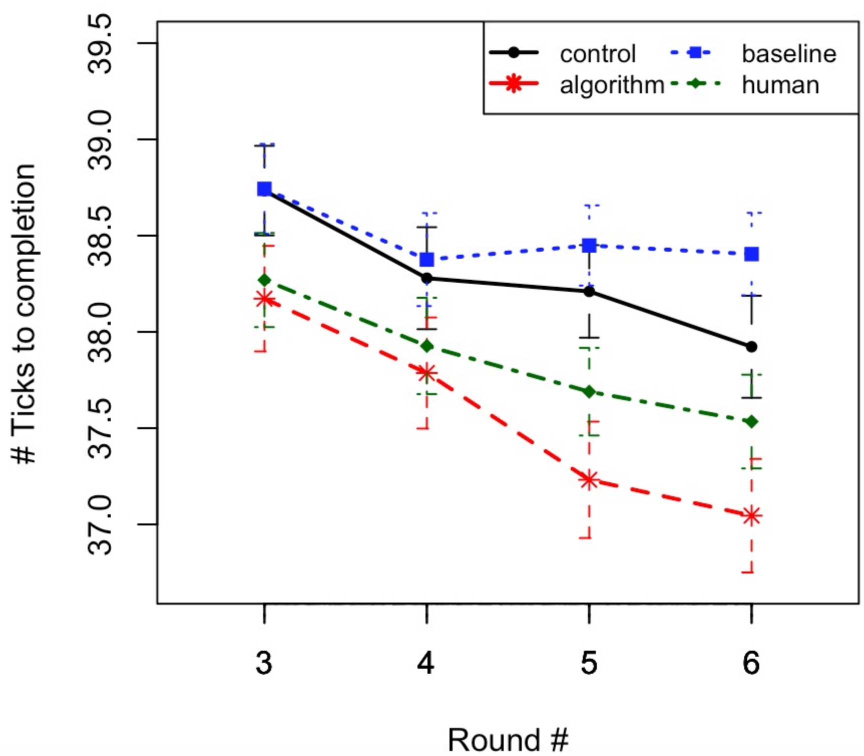


Amazon Mechanical Turk, N = 1,011

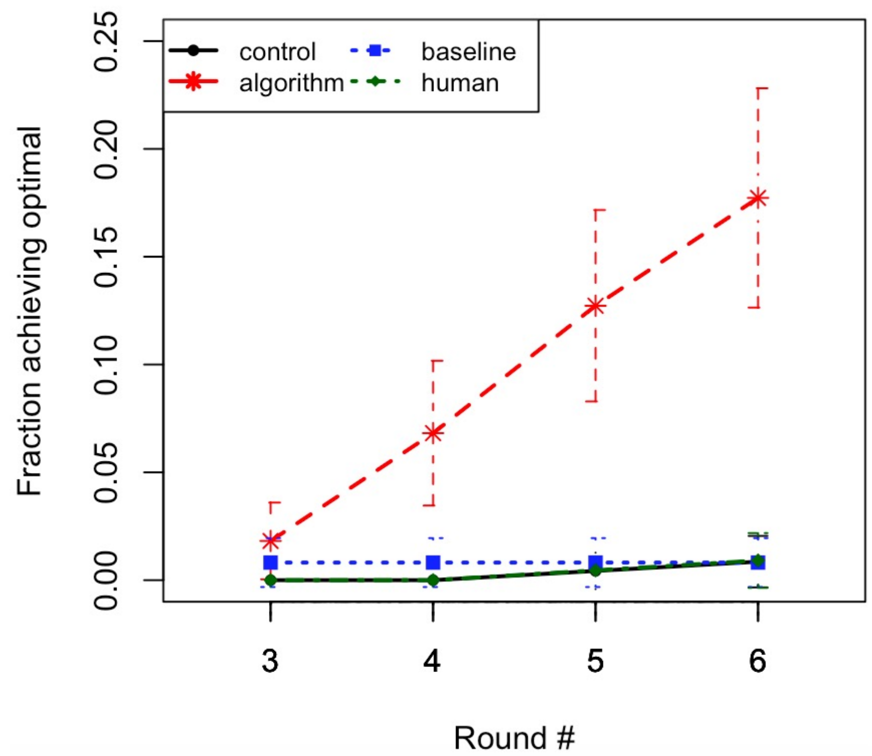
mean age 34.9, 60% female

Results Our Tip Helps Reach Optimal

\# Ticks to completion



Fraction achieving optimal

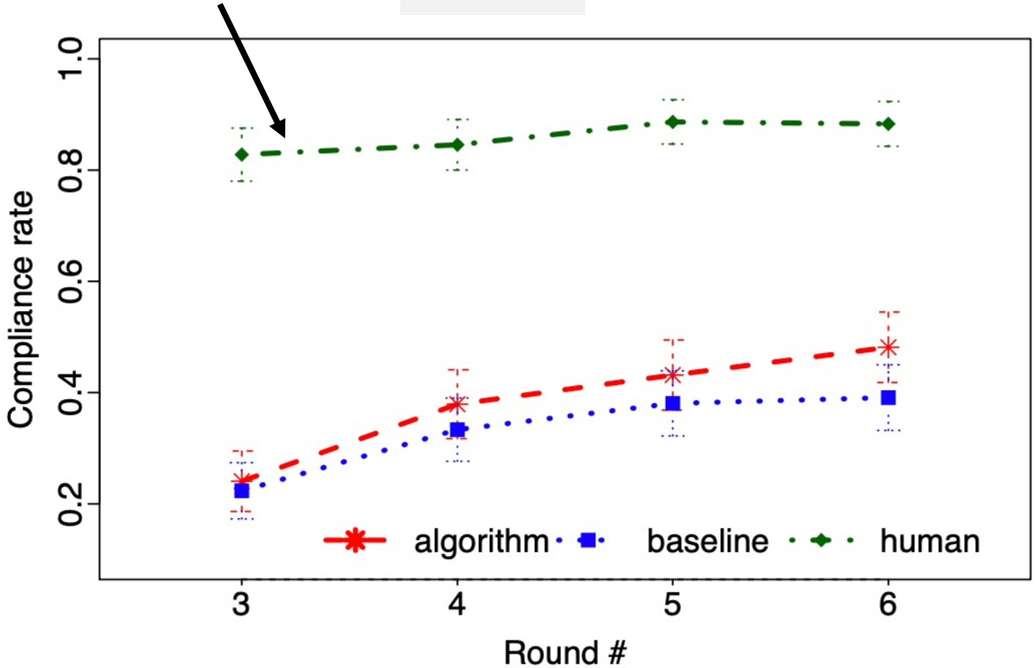


Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Results Compliance

Participants comply more with intuitive Human tip



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

26% Positive, 17% Negative

"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

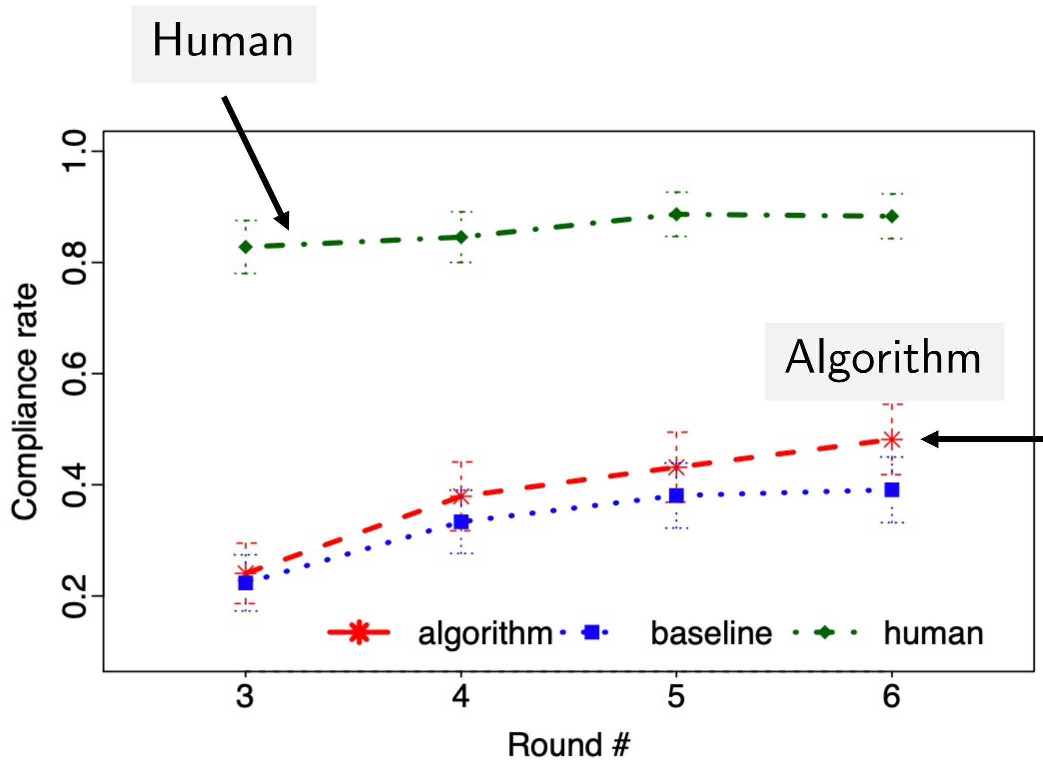
"I thought it was **smart** and I used it exclusively."

R_beijQ8guDyExa5r

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

R_1pA8wDYgWc9hblt

Results Against Counterintuitive Tips



23% Positive, **33% Negative**

"I didn't think it was right."

R_3EgrcrQouPcb1fS

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

R_10HkPUkR6o0qDFT

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

R_2YD5x6BL7mhCYEP

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

R_2s0UA1omAifrFgx

Amazon Mechanical Turk, N = 1,011

mean age 34.9, 60% female

Results Learning Beyond Tips

Structure of Optimal Policy

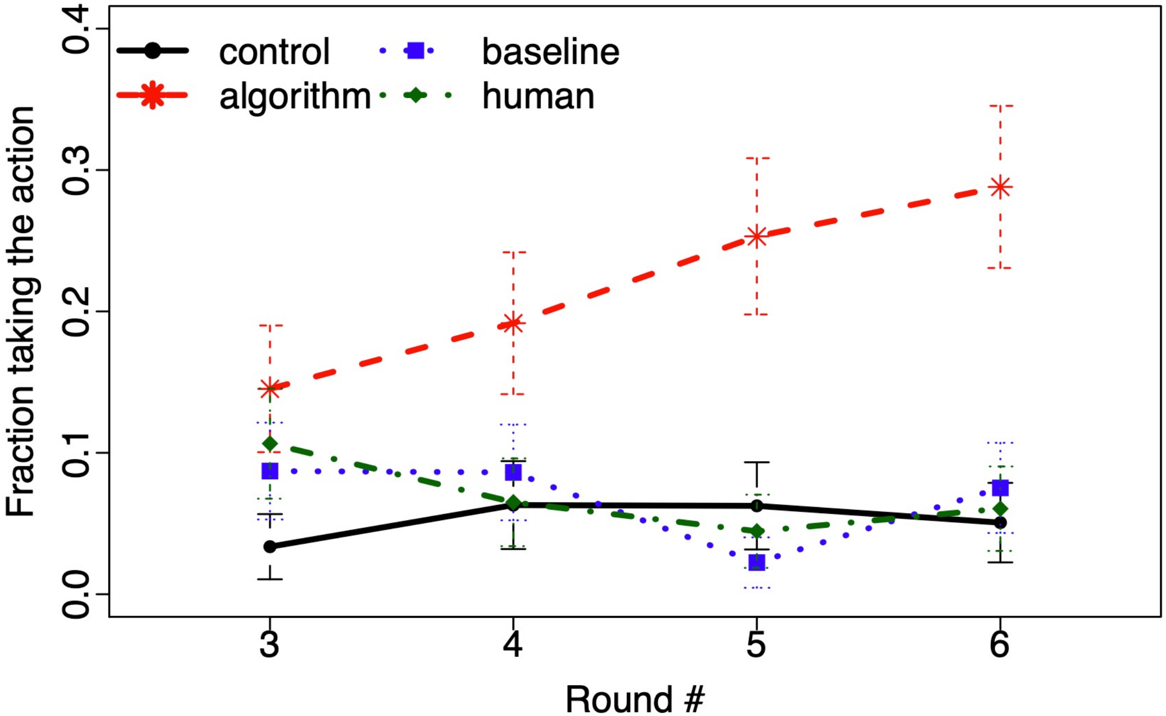
		Chop	Cook	Plate	
Sous-Chef	2	3	2	2	times
Server	3	1	2	2	times

Algorithm Baseline

Results Learning Beyond Tips

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

Sous-Chef chops 3 times



Amazon Mechanical Turk, N = 1,011
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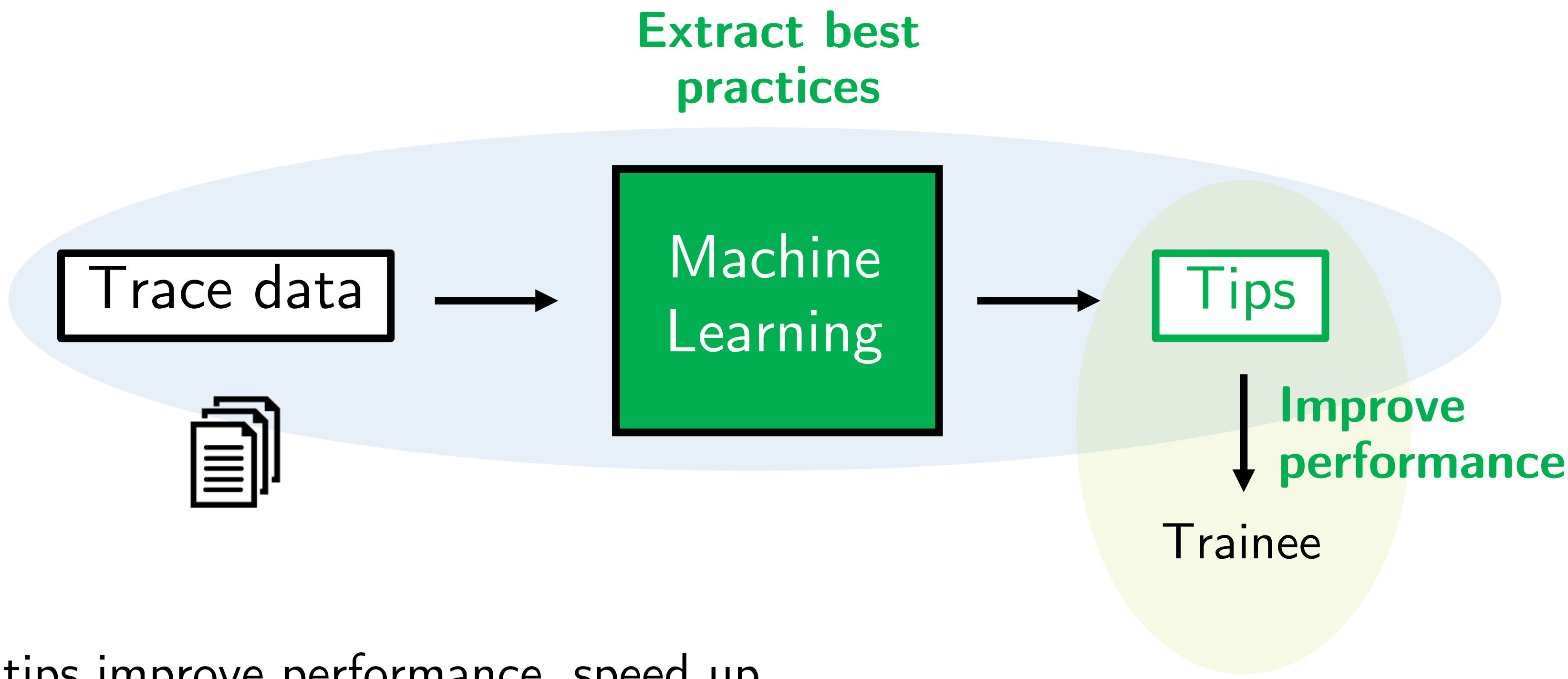
Summary

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

Hamsa Bastani, Osbert Bastani, **Park Sinchaisri** (parksinchaisri@berkeley.edu/ wichinpong.com)

Potential Issues

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