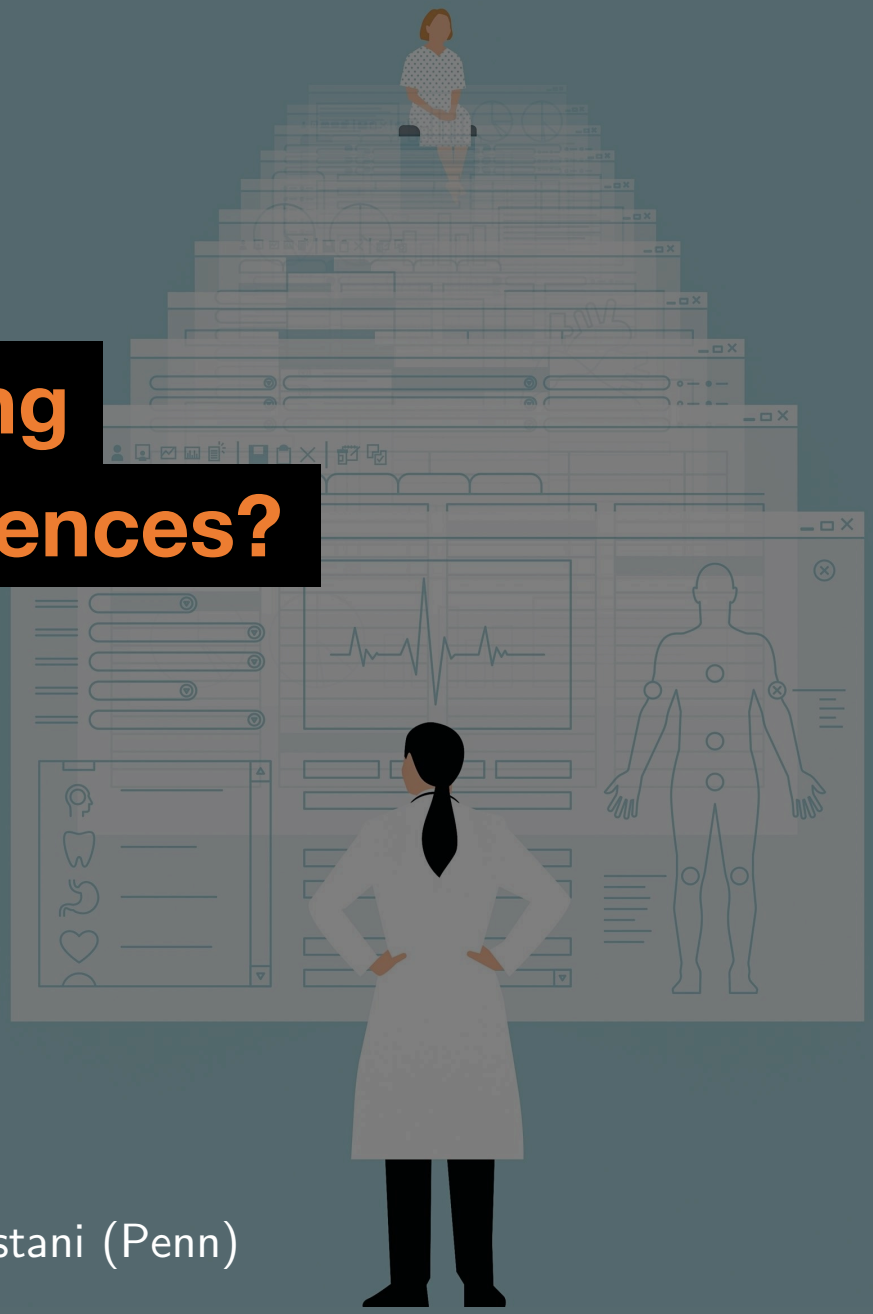
Learning Best Practices

Can Machine Learning Substitute for Experiences?

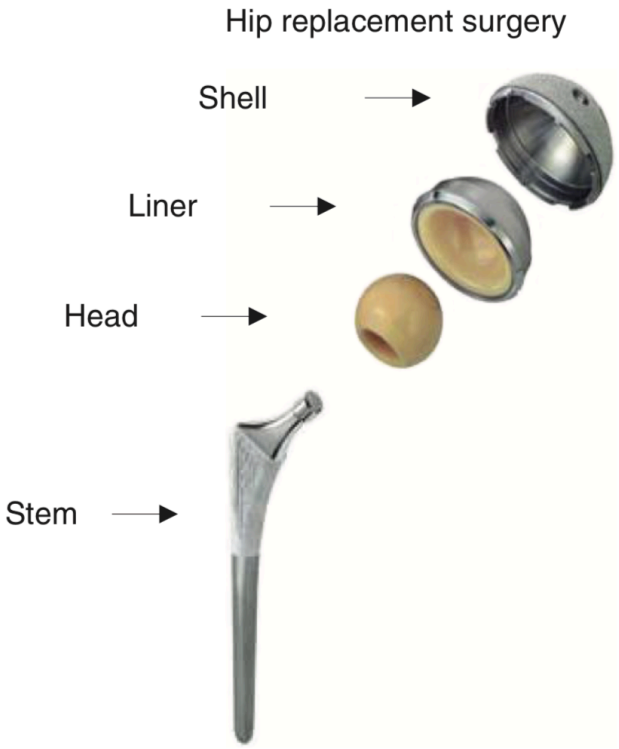


INFORMS 2019

Park Sinchaisri (Wharton)
with Hamsa Bastani (Wharton), Osbert Bastani (Penn)

Learning Takes Time

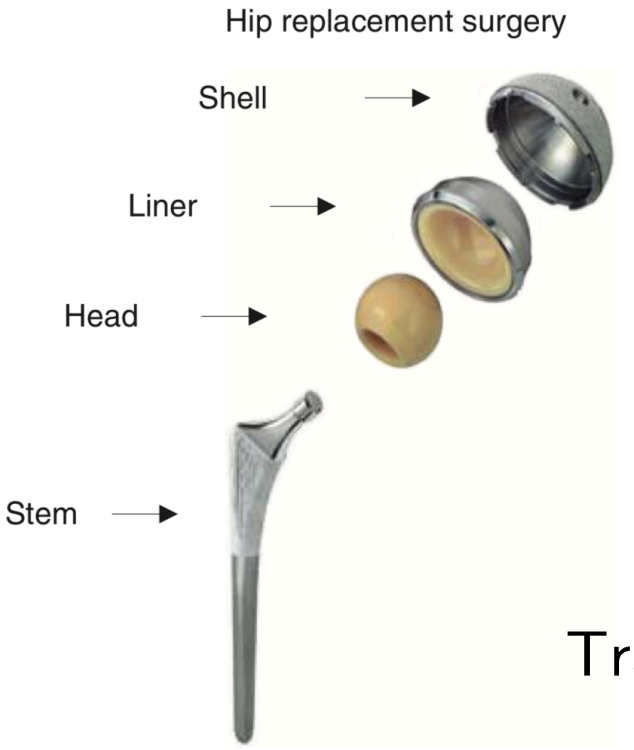
Learning Takes Time



"The first use of certain device versions can result in at least a **32.4% increase in surgery duration**, hurting quality and productivity."

- Ramdas et al. 2018

Learning Takes Time

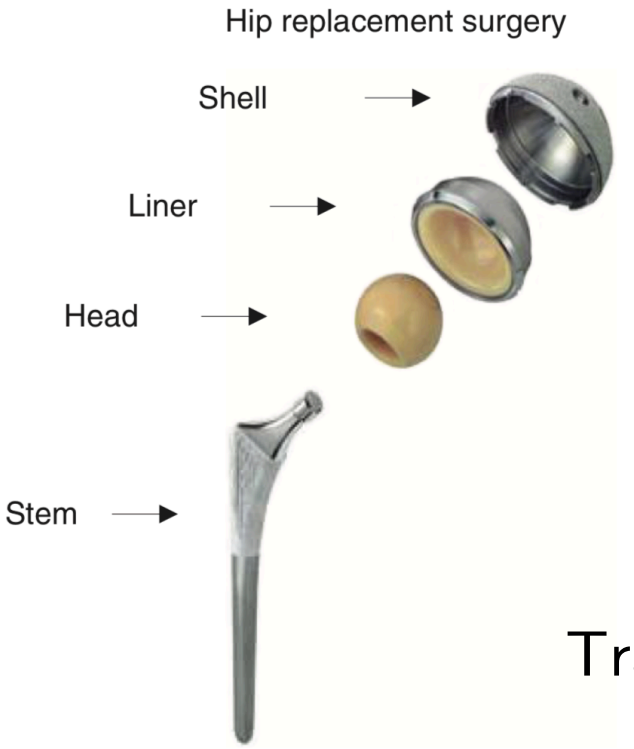


"The first use of certain device versions can result in at least a **32.4% increase in surgery duration**, hurting quality and productivity."

- Ramdas et al. 2018

Training workers is really important, but there is a big cost upfront.

Learning Takes Time



"The first use of certain device versions can result in at least a **32.4% increase in surgery duration**, hurting quality and productivity."

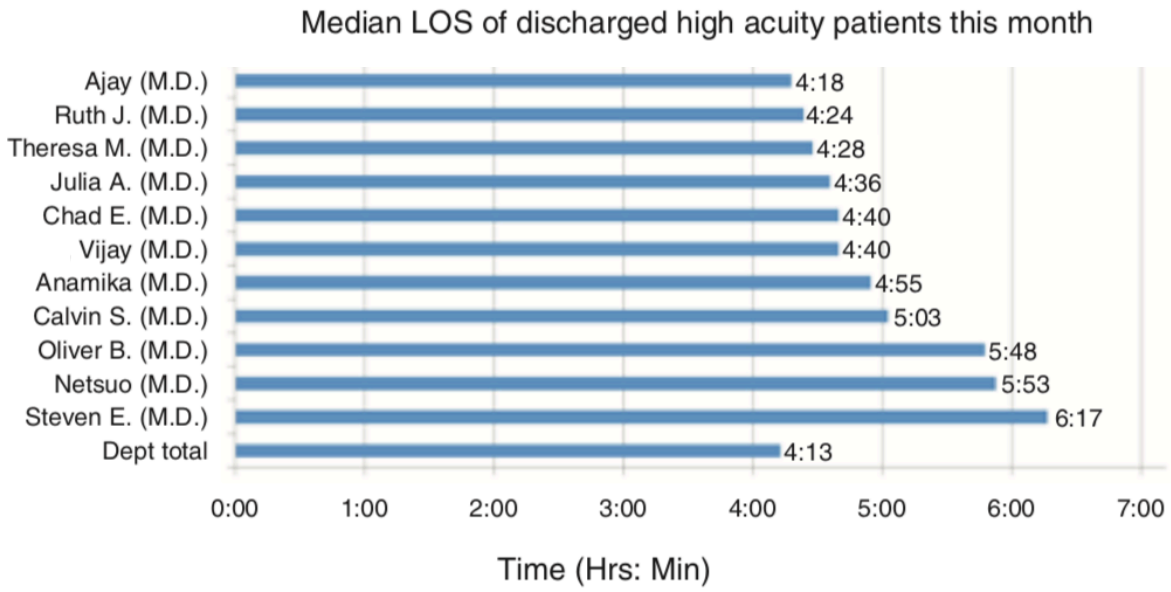
- Ramdas et al. 2018

Training workers is really important, but there is a big cost upfront.

Simple Tips?

Learning from Experts

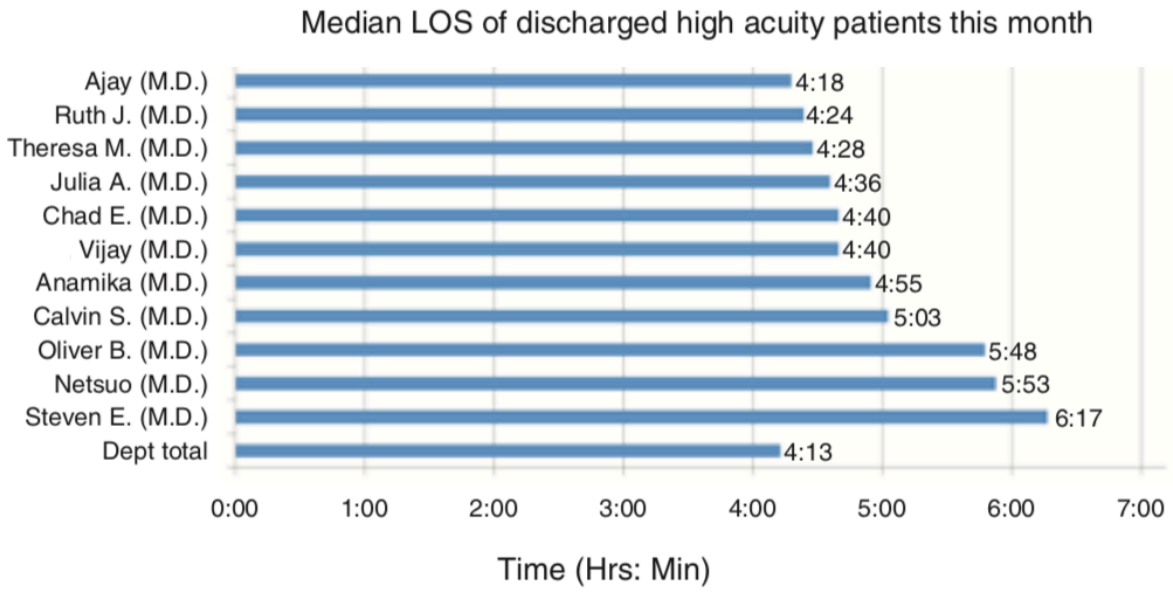
Learning from Experts



"The public disclosure of RPF allowed workers to **identify their top-performing coworkers**, which in turn enabled the identification and validation of **best practices**..."

- Song et al. 2018

Learning from Experts



"The public disclosure of RPF allowed workers to **identify their top-performing coworkers**, which in turn enabled the identification and validation of **best practices**..."

- Song et al. 2018

But It's Still Hard

Trace Data is Everywhere

Trace Data is Everywhere

Physicians

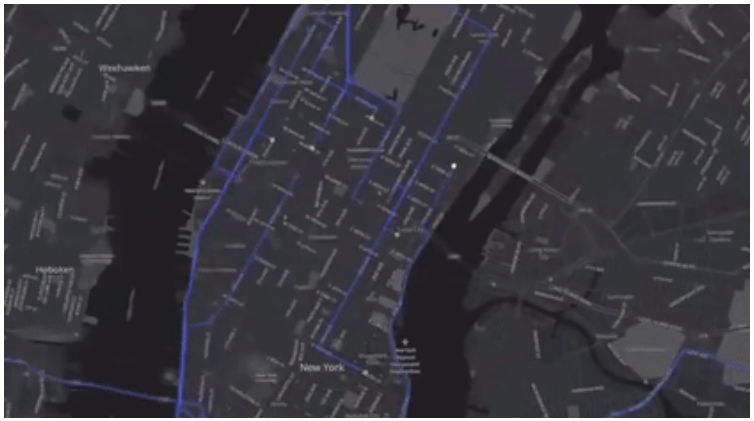
☐	• ROACH,TRISTIN	Lipitor 80 mg		MILLER,ALEX,MD *status: Unreviewed*	05•18•17
☐	• LEON,ERIN	Geriatric Wellness Visit		JONES,CAMERON,MD *status: Unreviewed*	05•16•17
☐	• BECK,ALIVIA	Zocor 20 mg		JACK,JACK,MD *status: Unreviewed, held*	05•18•17
☐	NORTON,BETHANY	Norvasc 10 mg		MILLER,ALEX,MD *status: Unreviewed*	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
☐	BERN,MARC	Office Visit - Itemized Conditions		JONES,CAMERON,MD *status: Unreviewed*	05•12•17
☐	ANDERSON,JIM	Advanced Directives Advanced Directives Addendum		JONES,CAMERON,MD *status: Unreviewed*	05•12•17
☐	BECKER,JOSEPH	Office Visit1		JONES,CAMERON,MD *status: Unreviewed*	05•02•17
☐	HANSEN,GEORGE	Office Visit1		JONES,CAMERON,MD *status: Unreviewed*	05•02•17
☐	FALK,MICHAEL A	Urine Albumin/Creatinine, Urine C & S AMD_996304_74		SMITH,TRACY,MD *status: Unreviewed*	05•02•17

Trace Data is Everywhere

Physicians

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
BERN,MARC	Office Visit - Itemized Conditions		JONES,CAMERON,MD *status: Unreviewed*	05•12•17
ANDERSON,JIM	Advanced Directives Advanced Directives Addendum		JONES,CAMERON,MD *status: Unreviewed*	05•12•17
BECKER,JOSEPH	Office Visit1		JONES,CAMERON,MD *status: Unreviewed*	05•02•17
HANSEN,GEORGE	Office Visit1		JONES,CAMERON,MD *status: Unreviewed*	05•02•17
FALK,MICHAEL A	Urine Albumin/Creatinine, Urine C & S AMD_996304_74		SMITH,TRACY,MD *status: Unreviewed*	05•02•17

Uber Drivers



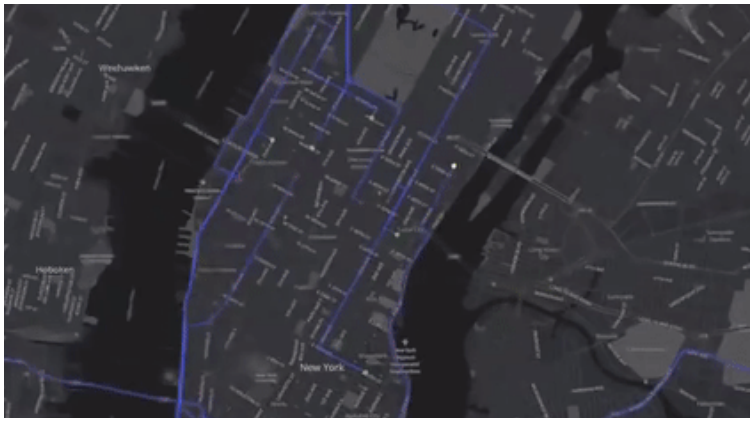
Whong 2014

Trace Data is Everywhere

Physicians

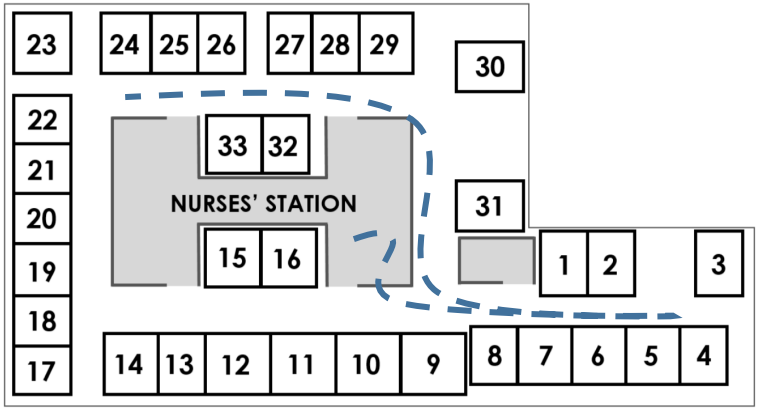
ROACH,TRISTIN	Lipitor 80 mg		MILLER,ALEX,MD status: Unreviewed	05•18•17
LEON,ERIN	Geriatric Wellness Visit		JONES,CAMERON,MD status: Unreviewed	05•16•17
BECK,ALIVIA	Zocor 20 mg		JACK,JACK,MD status: Unreviewed, held	05•18•17
NORTON,BETHANY	Norvasc 10 mg		MILLER,ALEX,MD status: Unreviewed	05•18•17
MONTGOMERY,BLAINE	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
BERN,MARC	Office Visit - Itemized Conditions		JONES,CAMERON,MD status: Unreviewed	05•12•17
ANDERSON,JIM	Advanced Directives Advanced Directives Addendum		JONES,CAMERON,MD status: Unreviewed	05•12•17
BECKER,JOSEPH	Office Visit1		JONES,CAMERON,MD status: Unreviewed	05•02•17
HANSEN,GEORGE	Office Visit1		JONES,CAMERON,MD status: Unreviewed	05•02•17
FALK,MICHAEL A	Urine Albumin/Creatinine, Urine C & S AMD_996304_74		SMITH,TRACY,MD status: Unreviewed	05•02•17

Uber Drivers



Whong 2014

Nurses



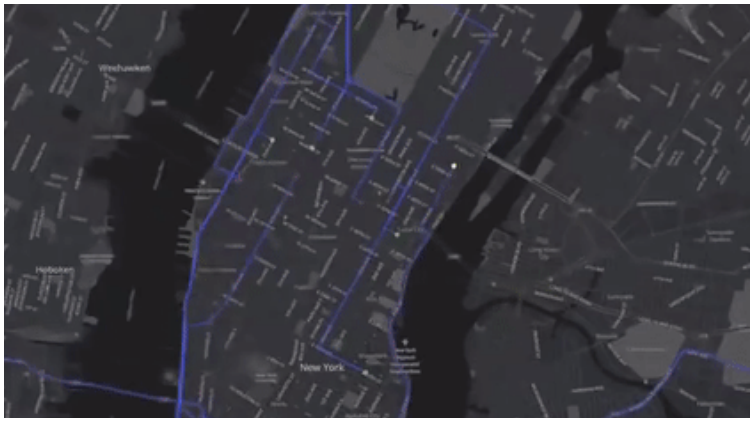
Meng et al. 2018

Trace Data is Everywhere

Physicians

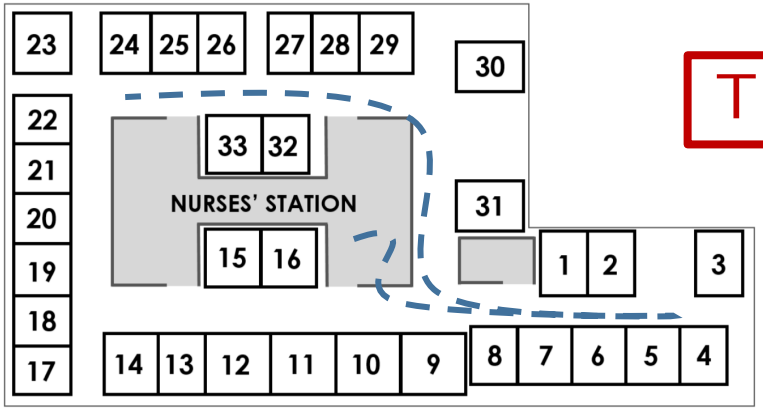
ROACH,TRISTIN	Lipitor 80 mg		MILLER,ALEX,MD status: Unreviewed	05•18•17
LEON,ERIN	Geriatric Wellness Visit		JONES,CAMERON,MD status: Unreviewed	05•16•17
BECK,ALIVIA	Zocor 20 mg		JACK,JACK,MD status: Unreviewed, held	05•18•17
NORTON,BETHANY	Norvasc 10 mg		MILLER,ALEX,MD status: Unreviewed	05•18•17
MONTGOMERY,BLAINE	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
BERN,MARC	Office Visit - Itemized Conditions		JONES,CAMERON,MD status: Unreviewed	05•12•17
ANDERSON,JIM	Advanced Directives Advanced Directives Addendum		JONES,CAMERON,MD status: Unreviewed	05•12•17
BECKER,JOSEPH	Office Visit1		JONES,CAMERON,MD status: Unreviewed	05•02•17
HANSEN,GEORGE	Office Visit1		JONES,CAMERON,MD status: Unreviewed	05•02•17
FALK,MICHAEL A	Urine Albumin/Creatinine, Urine C & S AMD_996304_74		SMITH,TRACY,MD status: Unreviewed	05•02•17

Uber Drivers



Whong 2014

Nurses



Meng et al. 2018

Trace data

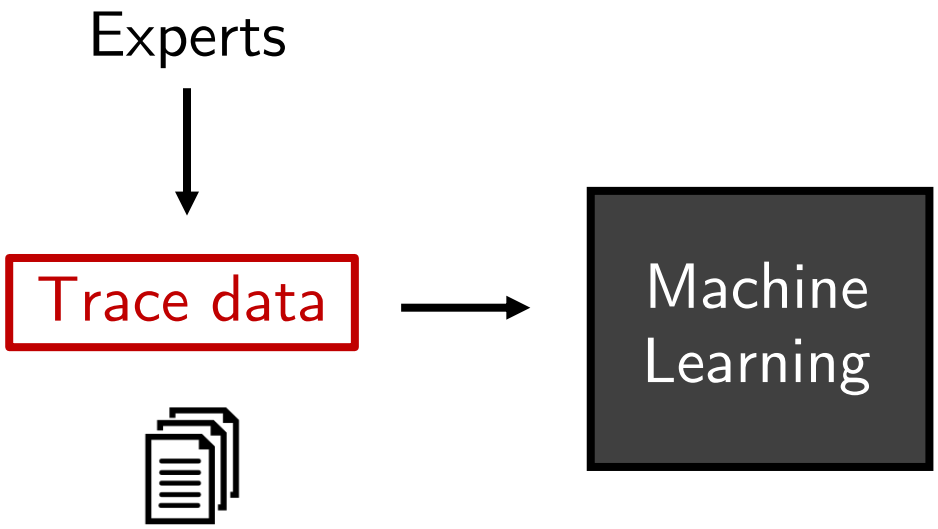
Tips

Our Paper

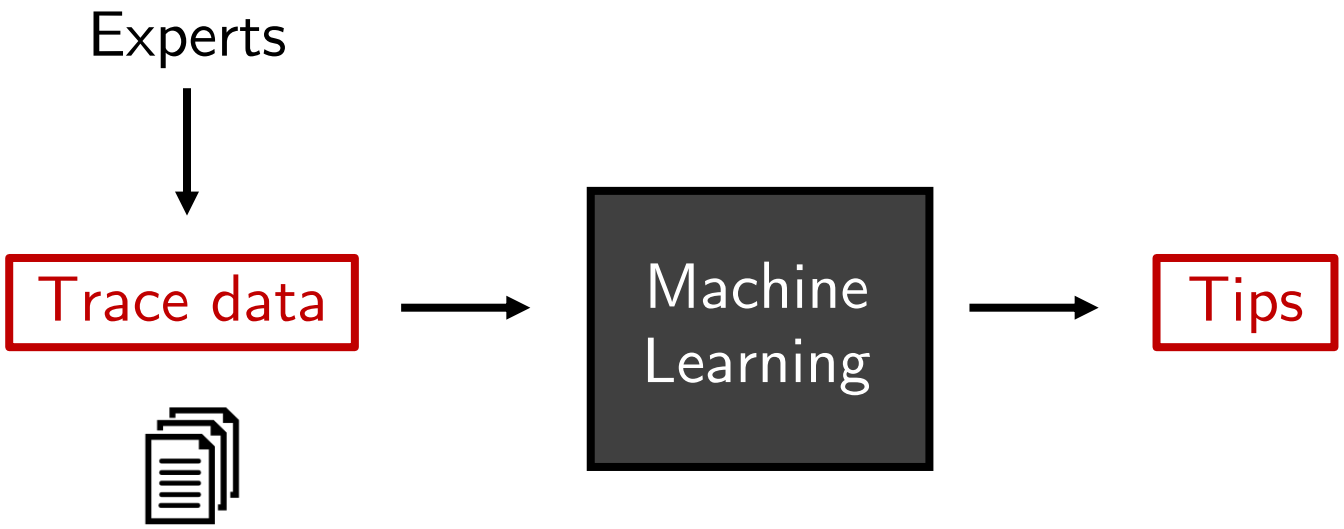
Experts

Trace data

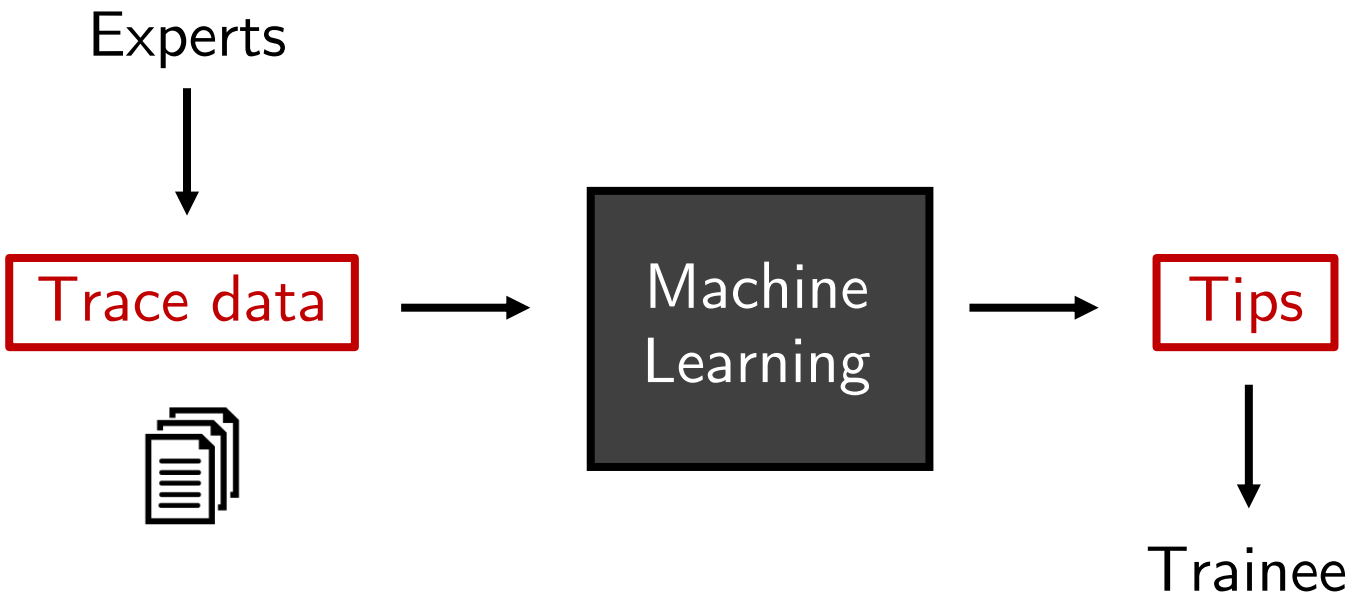
Our Paper



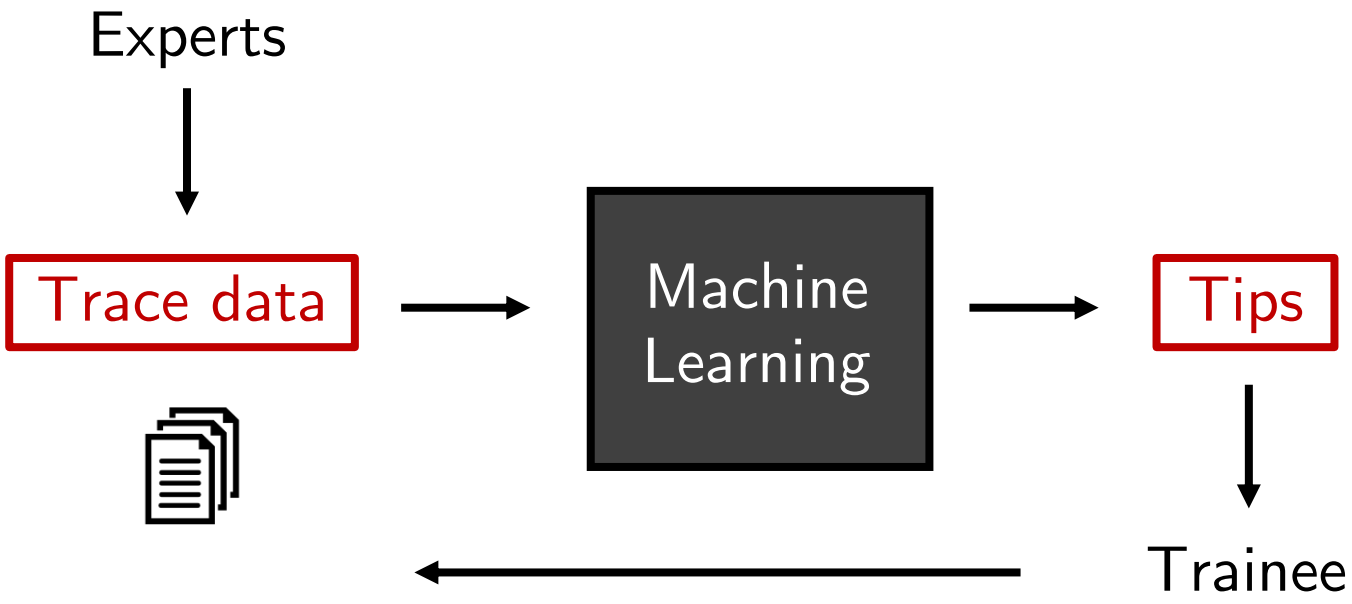
Our Paper



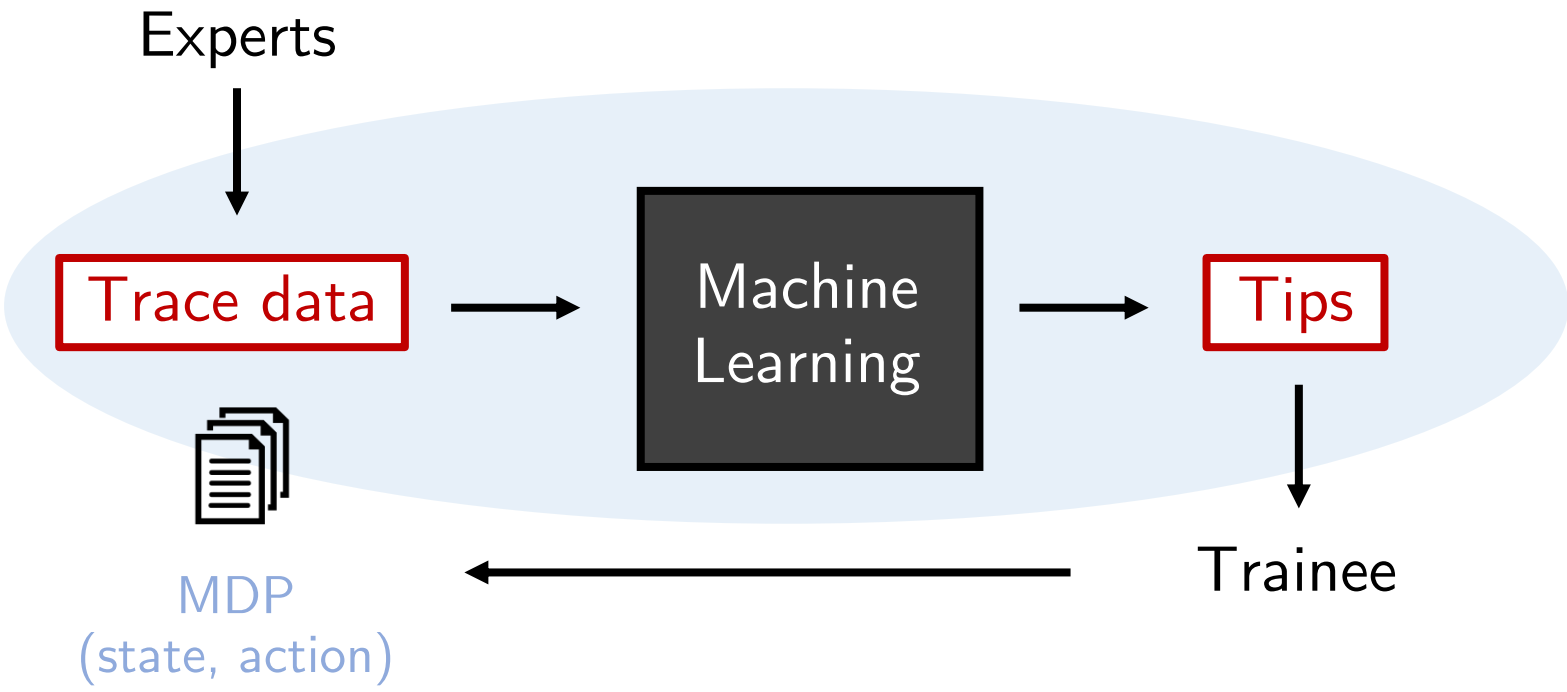
Our Paper



Our Paper

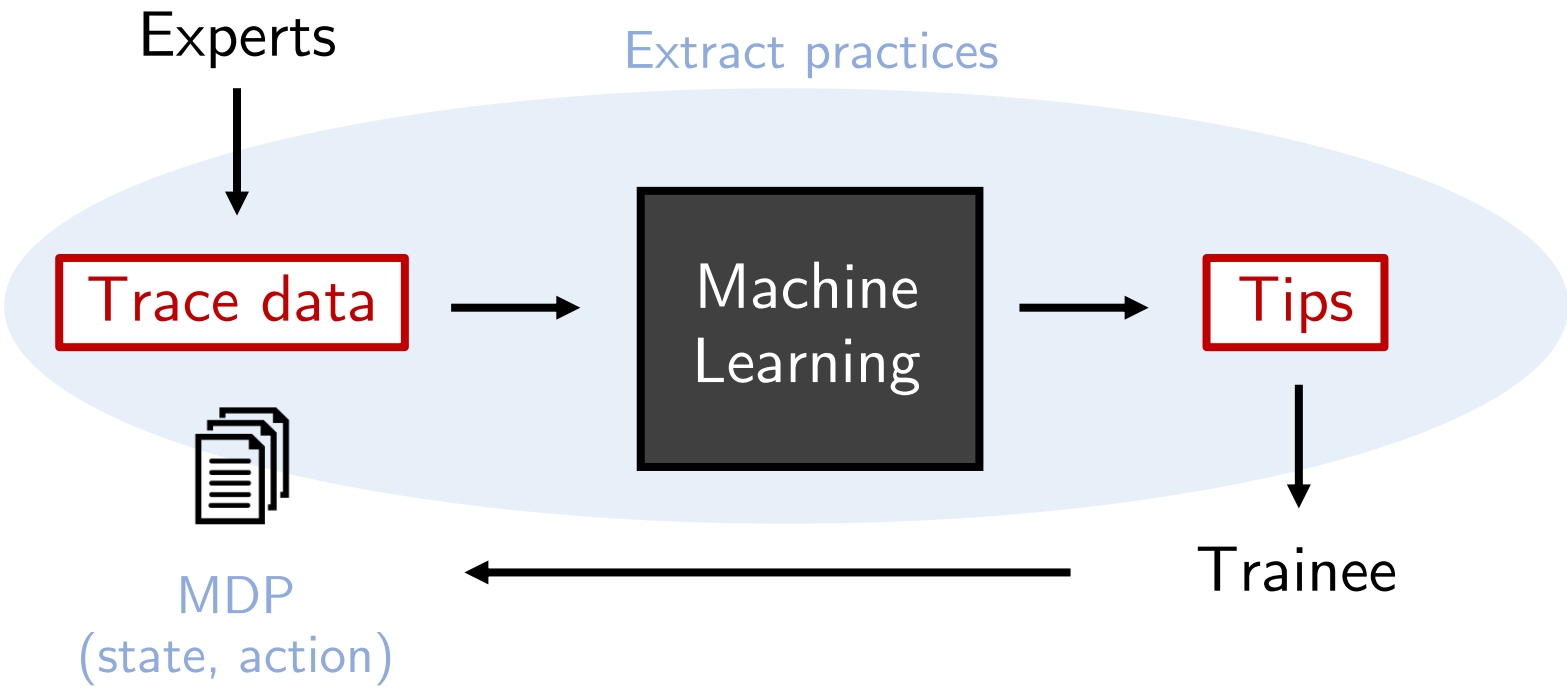


Our Paper



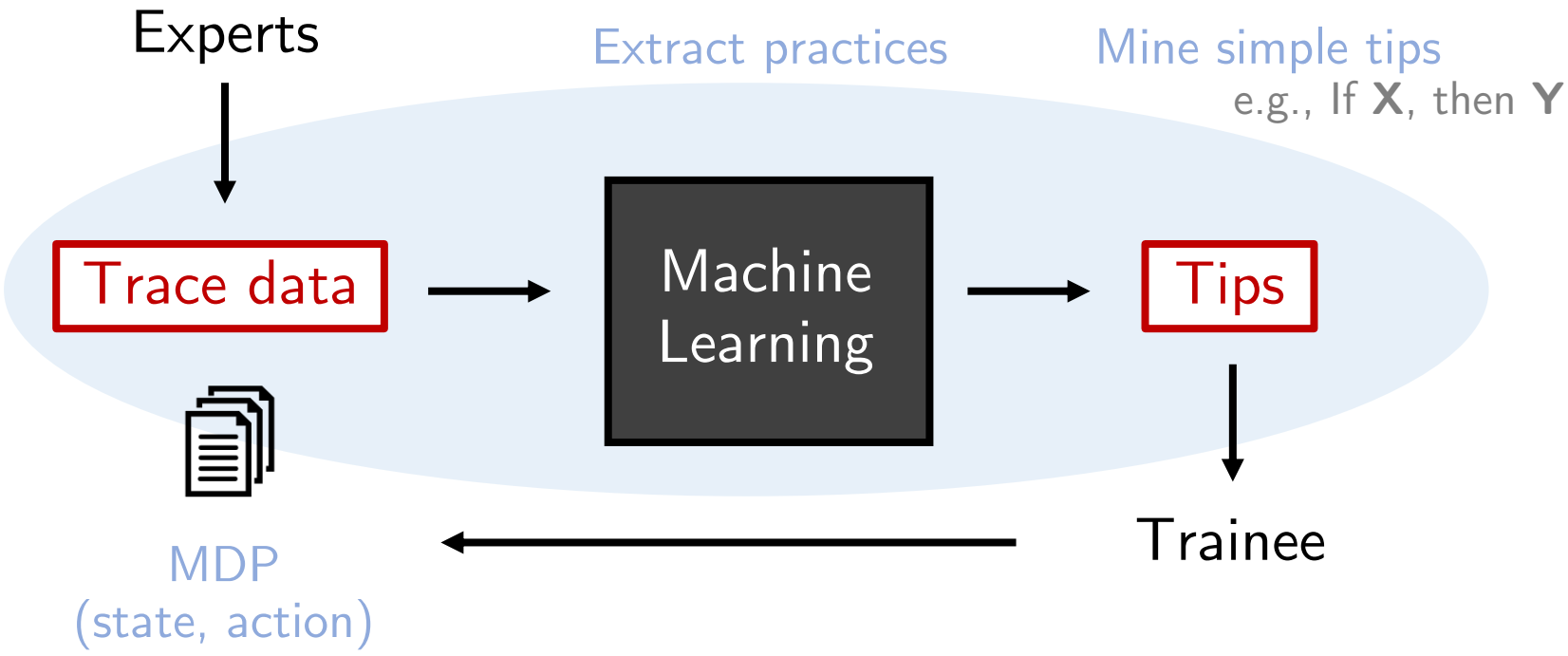
Today: Framework

Our Paper



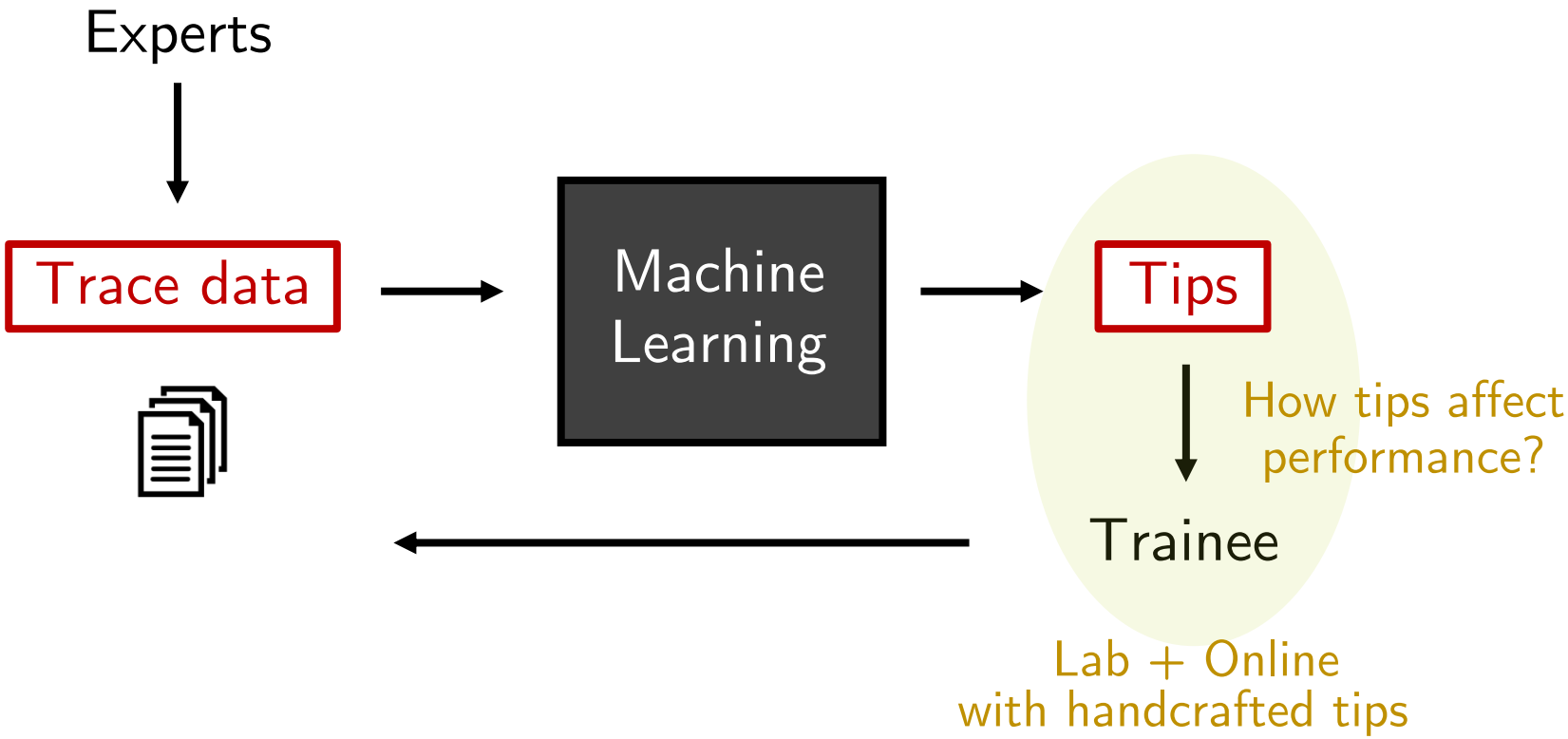
Today: Framework

Our Paper



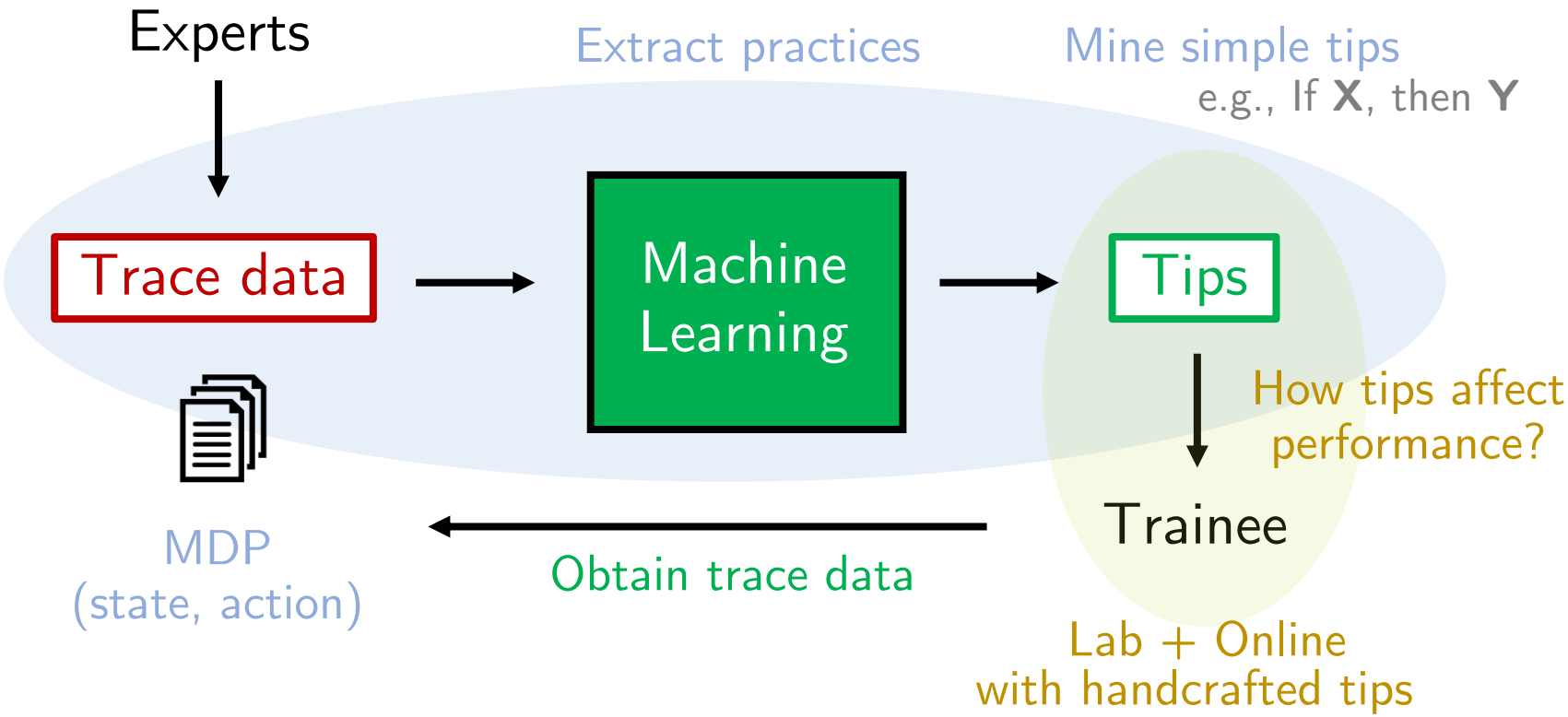
Today: Framework

Our Paper



Today: Framework Pilot Experiments

Our Paper



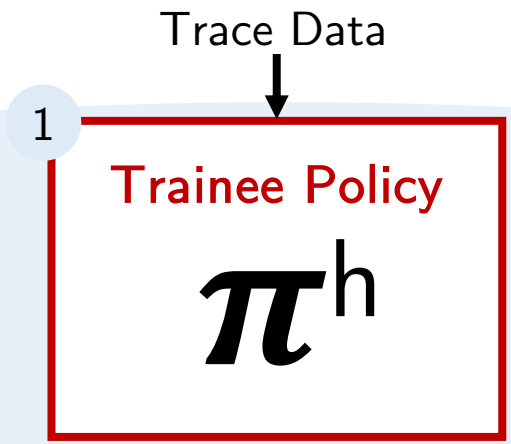
Today: Framework | Pilot Experiments | Results

Extracted practices + tips

Our Framework

Policy = the probability distribution of actions given a state

Our Framework

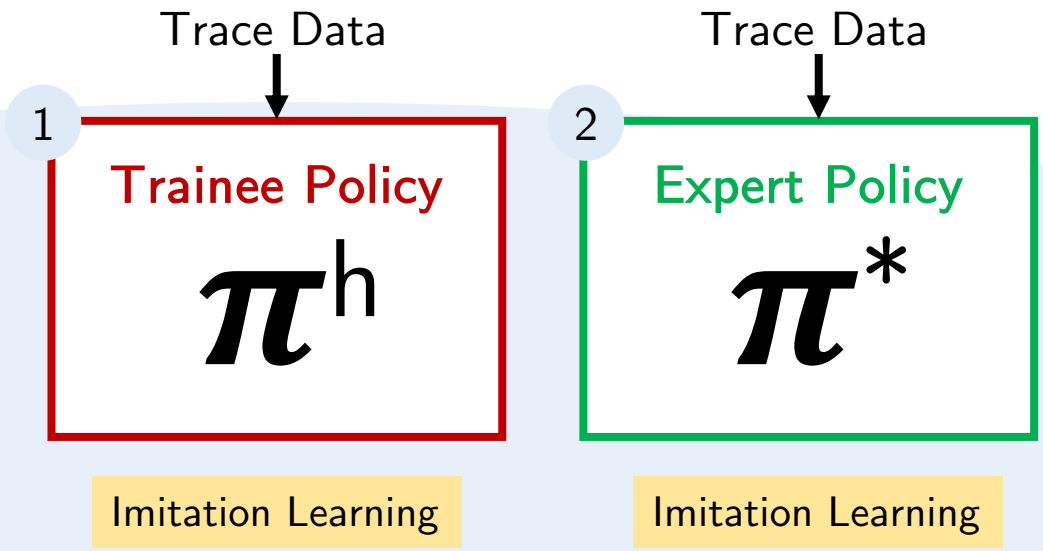


Policy = the probability distribution of actions given a state

Imitation Learning

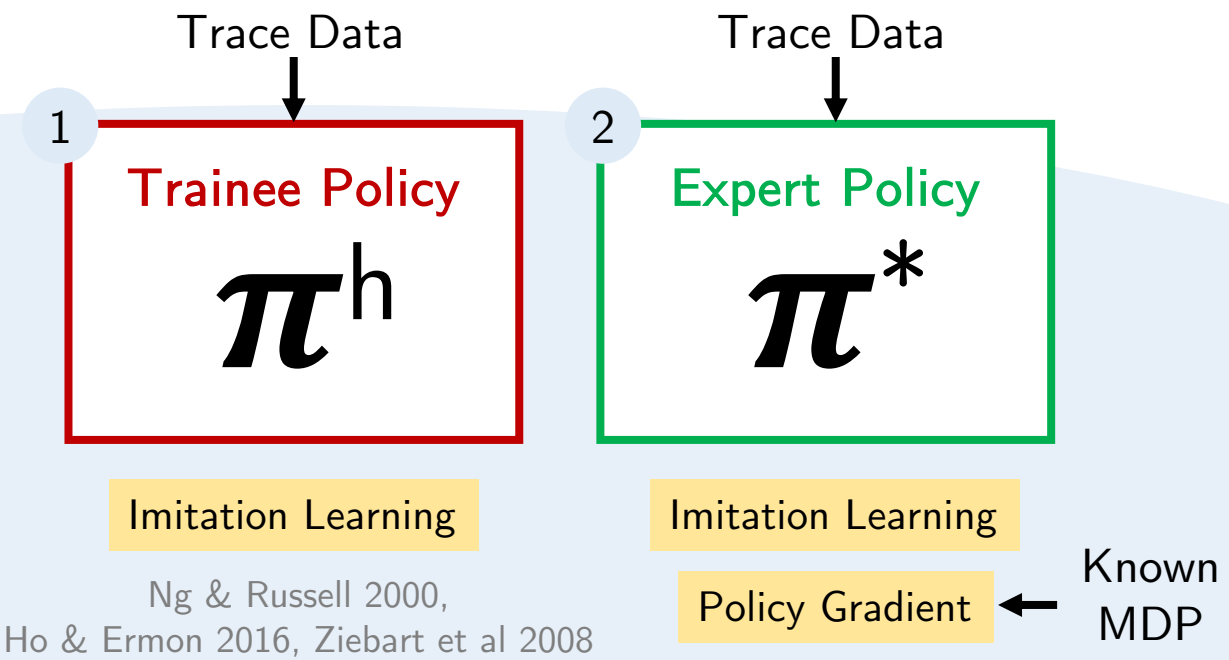
Ng & Russell 2000,
Ho & Ermon 2016, Ziebart et al 2008

Our Framework

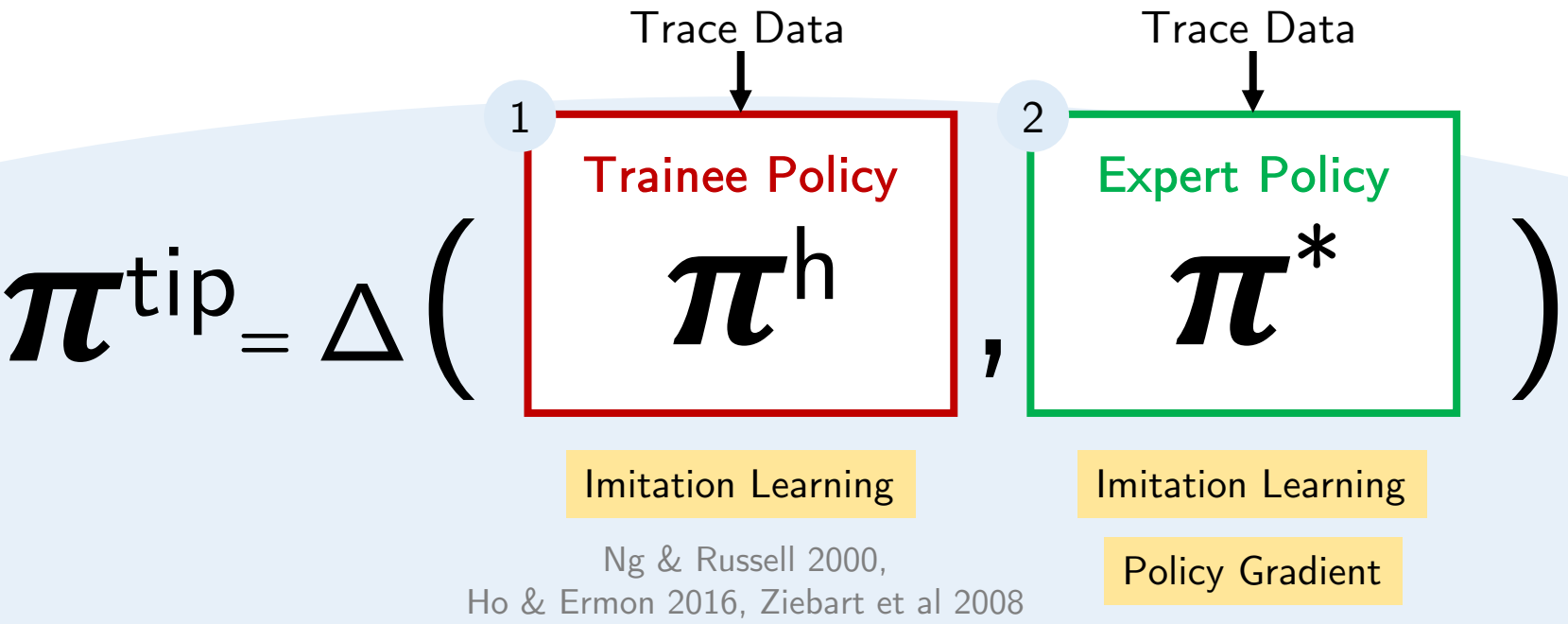


Ng & Russell 2000,
Ho & Ermon 2016, Ziebart et al 2008

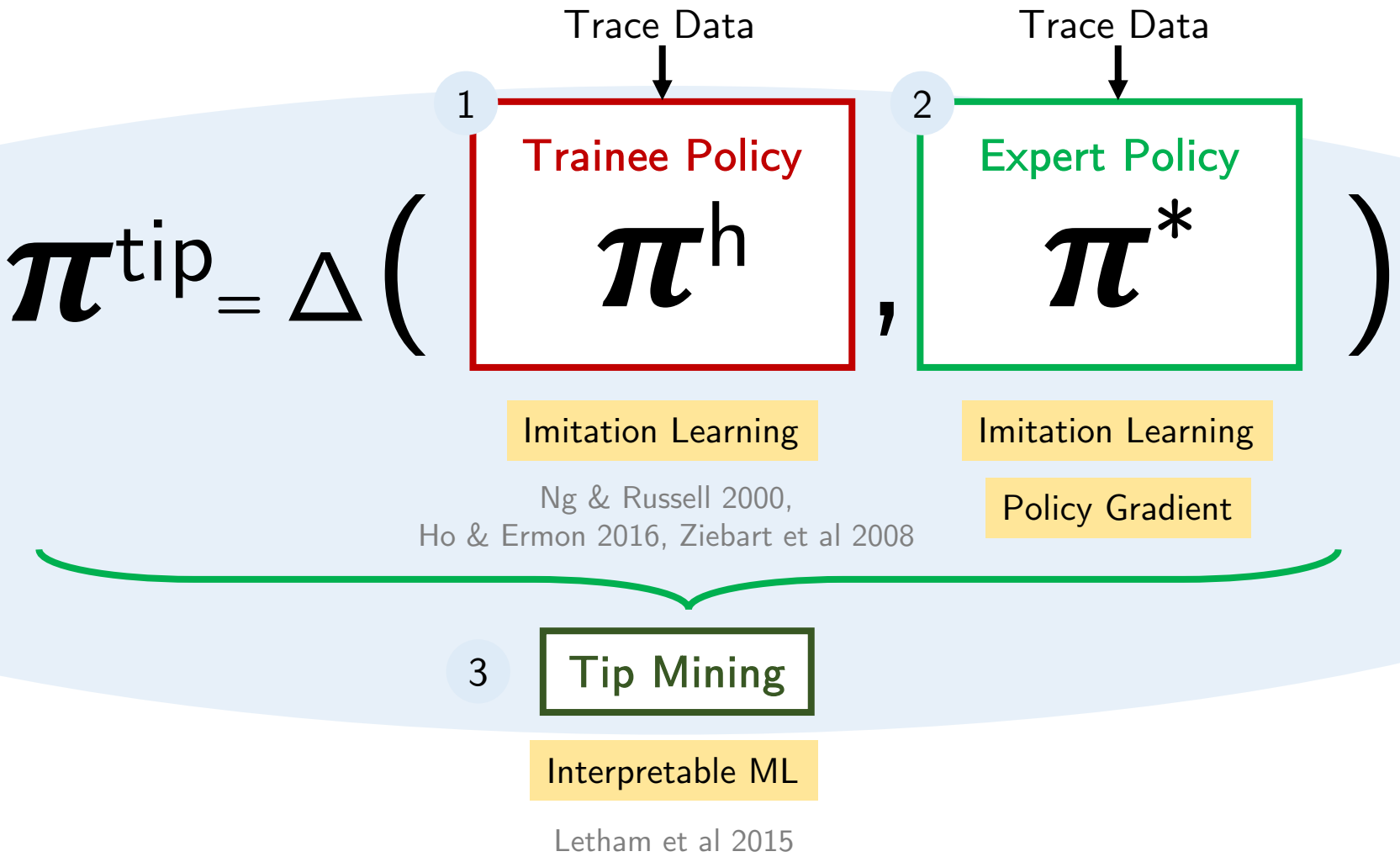
Our Framework



Our Framework



Our Framework



Learning Trainee Policy

- Supervised Learning
  - Random Forests/
    Gradient Boosting Machine

1

Trainee Policy

π^h

State ⟶ Action

Learning Trainee Policy

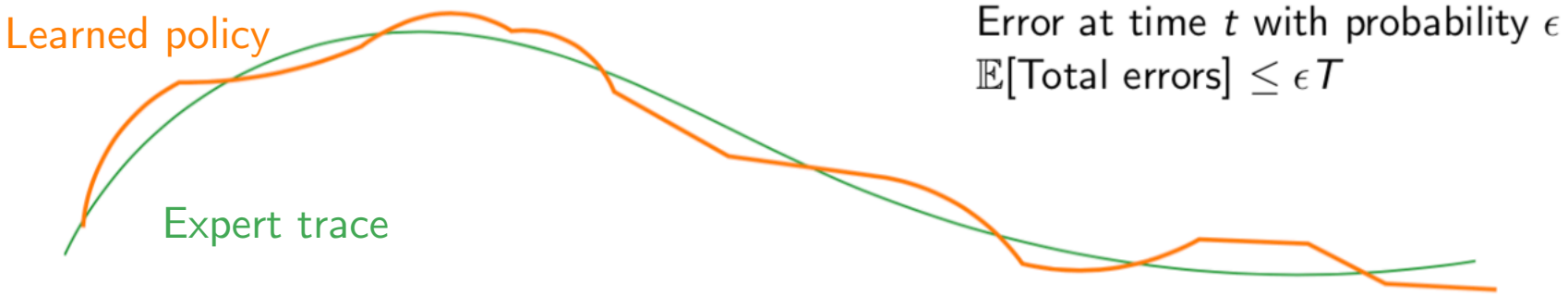
- Supervised Learning
  - Random Forests/
    Gradient Boosting Machine

1

Trainee Policy

π^h

State ⟶ Action



Learning Trainee Policy

1

Trainee Policy

π^h

- Supervised Learning
  - Random Forests/
    Gradient Boosting Machine

State ⟶ Action

i.i.d. (state, action) pairs, ignores temporal structure

Learning Trainee Policy

- Supervised Learning
  - Random Forests/ Gradient Boosting Machine

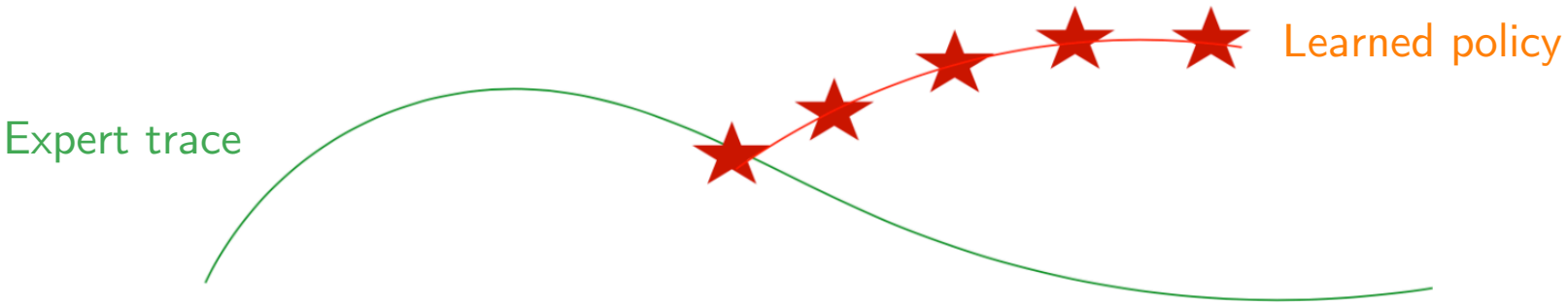
1

Trainee Policy

π^h

State ⟶ Action

i.i.d. (state, action) pairs, ignores temporal structure



Learning Trainee Policy

- Supervised Learning
  - Random Forests/ Gradient Boosting Machine

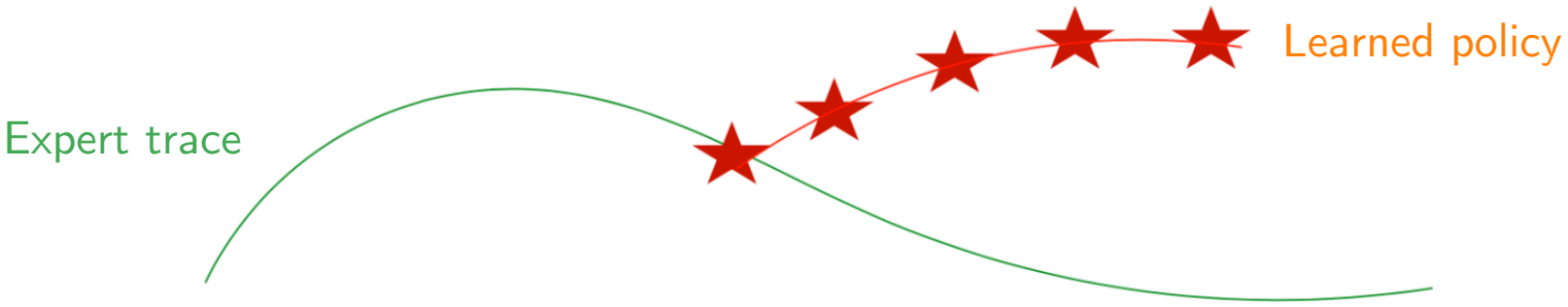
1

Trainee Policy

π^h

State ⟶ Action

i.i.d. (state, action) pairs, ignores temporal structure

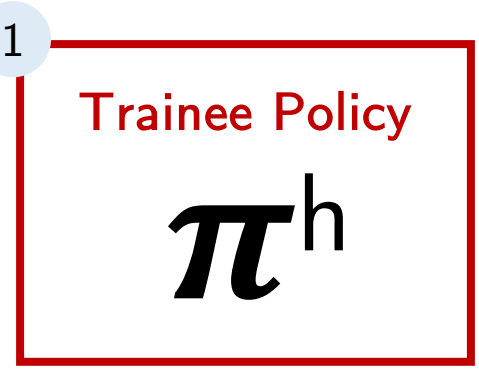


$\mathbb{E}[\text{Total errors}] \leq \epsilon(T + (T-1) + (T-2)\ldots + 1) \propto \epsilon T^2$

- Ross et al 2011

Imitation Learning

- Preserve (s,a) distribution
- Need human experts
  - Useful when it is easier for experts to demonstrate the desired behavior rather than:
    - Specifying a reward that would generate such behavior
    - Specifying the desired policy directly.



Imitation Learning

- Preserve (s,a) distribution
- Need human experts
  - Useful when it is easier for experts to demonstrate the desired behavior rather than:
    - Specifying a reward that would generate such behavior
    - Specifying the desired policy directly.
  - **Expensive!**

1

Trainee Policy

π^h

Imitation Learning

- Generative Adversarial IL
  - Distribution from trace data: $\mathbf{d}_{\pi \mathbf{h}}$

1

Trainee Policy

π^{h}

- Ho & Ermon 2016

Imitation Learning

- Generative Adversarial IL
  - Distribution from trace data: $\mathbf{d}_{\pi \mathbf{h}}$
  - Train a policy $\boldsymbol{\pi}^{\boldsymbol{\theta}}$ (gradient descent)
  - Obtain its (s, a) distribution: $\mathbf{d}_{\pi \boldsymbol{\theta}}$

1

Trainee Policy

$\boldsymbol{\pi}^{\mathrm{h}}$

- Ho & Ermon 2016

Imitation Learning

- Generative Adversarial IL
  - Distribution from trace data: $\mathbf{d}_{\pi \mathbf{h}}$
  - Train a policy $\boldsymbol{\pi}^{\boldsymbol{\theta}}$ (gradient descent)
  - Obtain its (s, a) distribution: $\mathbf{d}_{\pi \boldsymbol{\theta}}$
  - Find $\boldsymbol{\pi}^{\boldsymbol{\theta}}$ that minimizes $\mathbf{D}_{\mathbf{KL}}(\mathbf{d}_{\pi \boldsymbol{\theta}}, \mathbf{d}_{\pi \mathbf{h}})$

1

Trainee Policy

$\boldsymbol{\pi}^{\mathrm{h}}$

- Ho & Ermon 2016

Imitation Learning

1

Trainee Policy

π^{h}

- Generative Adversarial IL
  - Distribution from trace data: $\mathbf{d}_{\pi h}$
  - Train a policy π^{θ} (gradient descent)
  - Obtain its (s, a) distribution: $\mathbf{d}_{\pi\theta}$
  - Find π^{θ} that minimizes $\mathbf{D}_{KL}(\mathbf{d}_{\pi\theta}, \mathbf{d}_{\pi h})$

= States visited and actions taken in those states under π^{θ} to be to the same as those from π^{h}

- Ho & Ermon 2016

Learning Expert Policy

Reward function unknown

- Imitation learning from experts

2

Expert Policy

π^*

Learning Expert Policy

Expert Policy

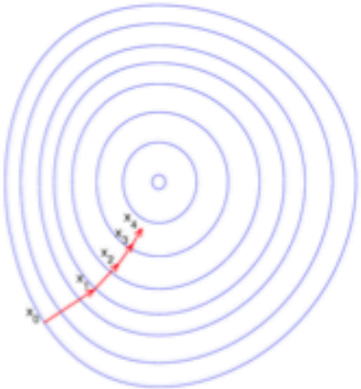
π^*

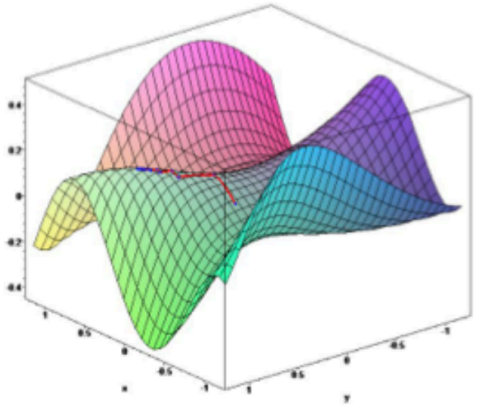
Reward function unknown

- Imitation learning from experts

Inferred reward function

- Our experiment: we know MDP.
- Solve for optimal policy with policy gradient algorithm





Learning Tips

3 Tip Mining

- Interpretable ML: Bayesian Rule Lists
  - Adapt from Letham et al 2015
  - If **[feature x],** then **[label y]**

Learning Tips

3 Tip Mining

- Interpretable ML: Bayesian Rule Lists
  - Adapt from Letham et al 2015
  - If **[feature x],** then **[label y]**

$$
\begin{aligned}
&\textbf{if} \quad\quad x \text{ obeys } a_1 \textbf{ then } y \sim \text{Binomial}(\theta_1),\ \theta_1 \sim \text{Beta}(\boldsymbol{\alpha} + \mathbf{N}_1)\\
&\textbf{else if } x \text{ obeys } a_2 \textbf{ then } y \sim \text{Binomial}(\theta_2),\ \theta_2 \sim \text{Beta}(\boldsymbol{\alpha} + \mathbf{N}_2)\\
&\vdots\\
&\textbf{else if } x \text{ obeys } a_m \textbf{ then } y \sim \text{Binomial}(\theta_m),\ \theta_m \sim \text{Beta}(\boldsymbol{\alpha} + \mathbf{N}_m)\\
&\textbf{else } y \sim \text{Binomial}(\theta_0),\ \theta_0 \sim \text{Beta}(\boldsymbol{\alpha} + \mathbf{N}_0).
\end{aligned}
$$

Learning Tips

3 Tip Mining

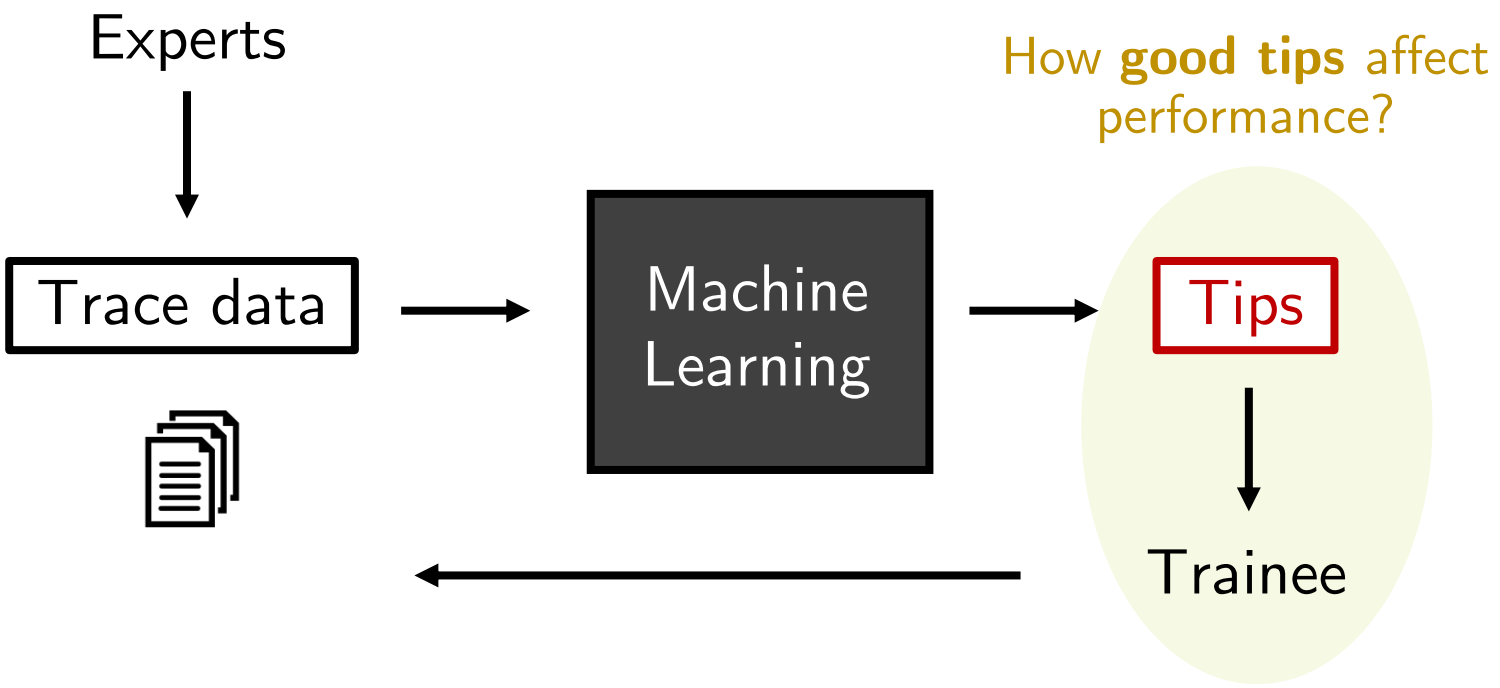
- Interpretable ML: Bayesian Rule Lists
  - Adapt from Letham et al 2015
  - If **[feature x],** then **[label y]**
  - e.g., if high blood pressure, then stroke
  - Pre-mined frequent patterns into a decision list using Bayesian statistics

Learning Tips

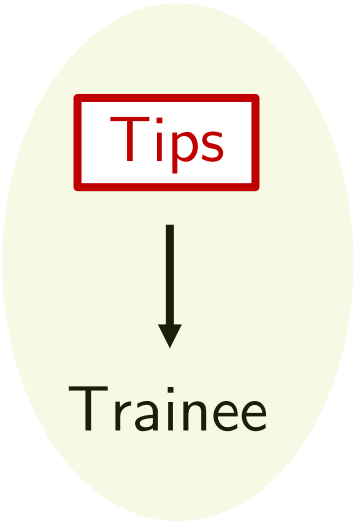
3 Tip Mining

- Interpretable ML: Bayesian Rule Lists
  - Adapt from Letham et al 2015
  - If **[feature x],** then **[label y]**
  - e.g., if high blood pressure, then stroke
  - Pre-mined frequent patterns into a decision list using Bayesian statistics

- Our context
  - If **[state s]**, then take **[action a]**


Experts
How **good tips** affect performance?
Trace data
Machine Learning
Tips
Trainee

How **good tips** affect performance?

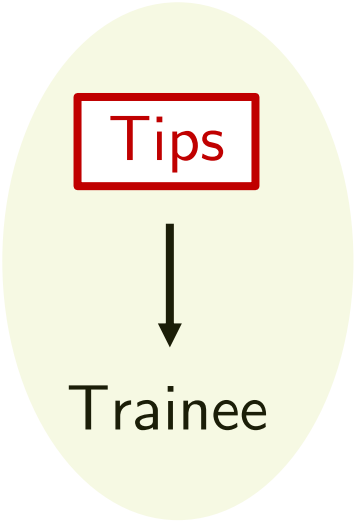


Pilot Experiments

Queueing Game

How **good tips** affect performance?

Start with handcrafted tips



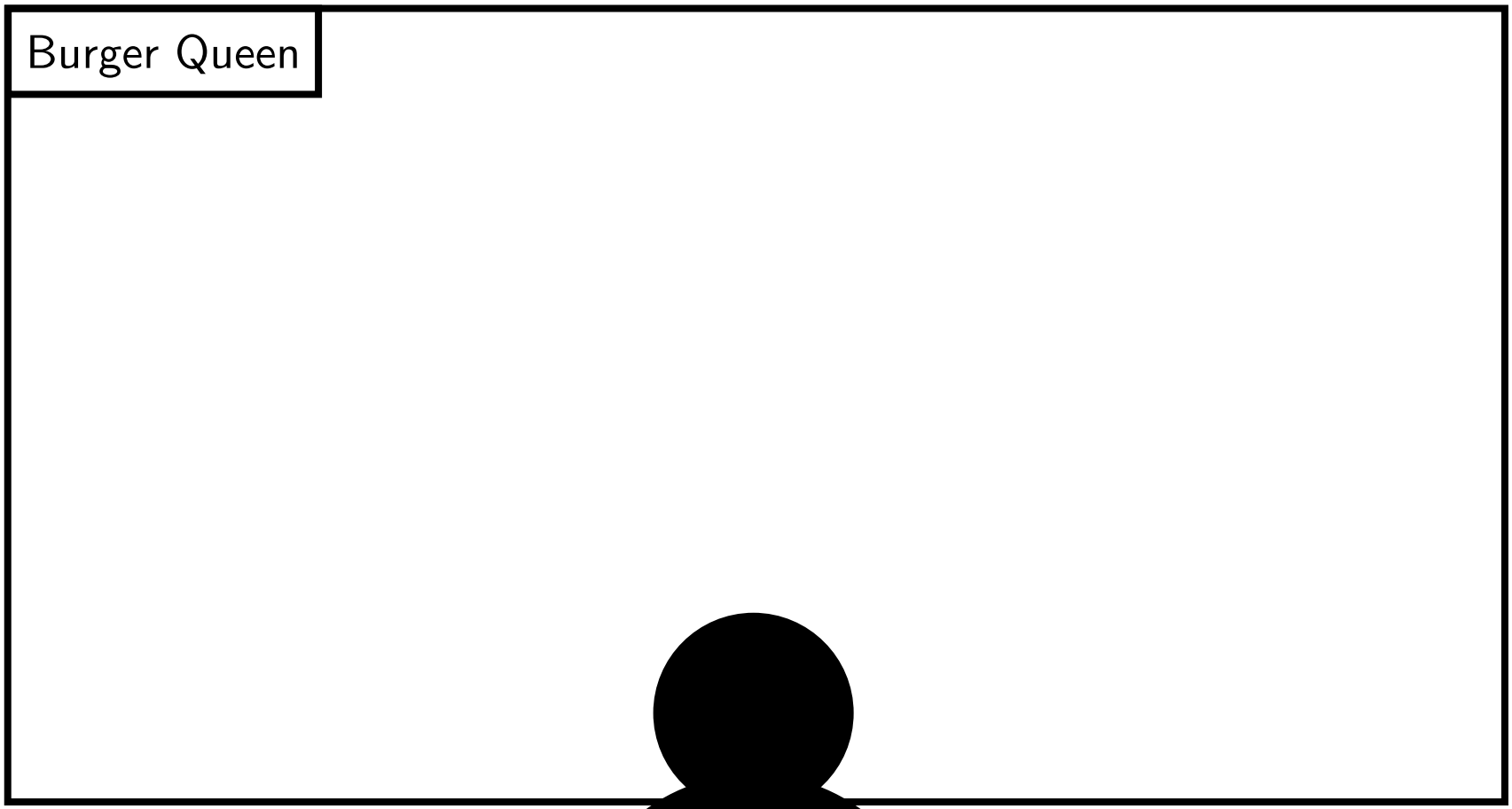
Amazon Mechanical Turk

N = 146

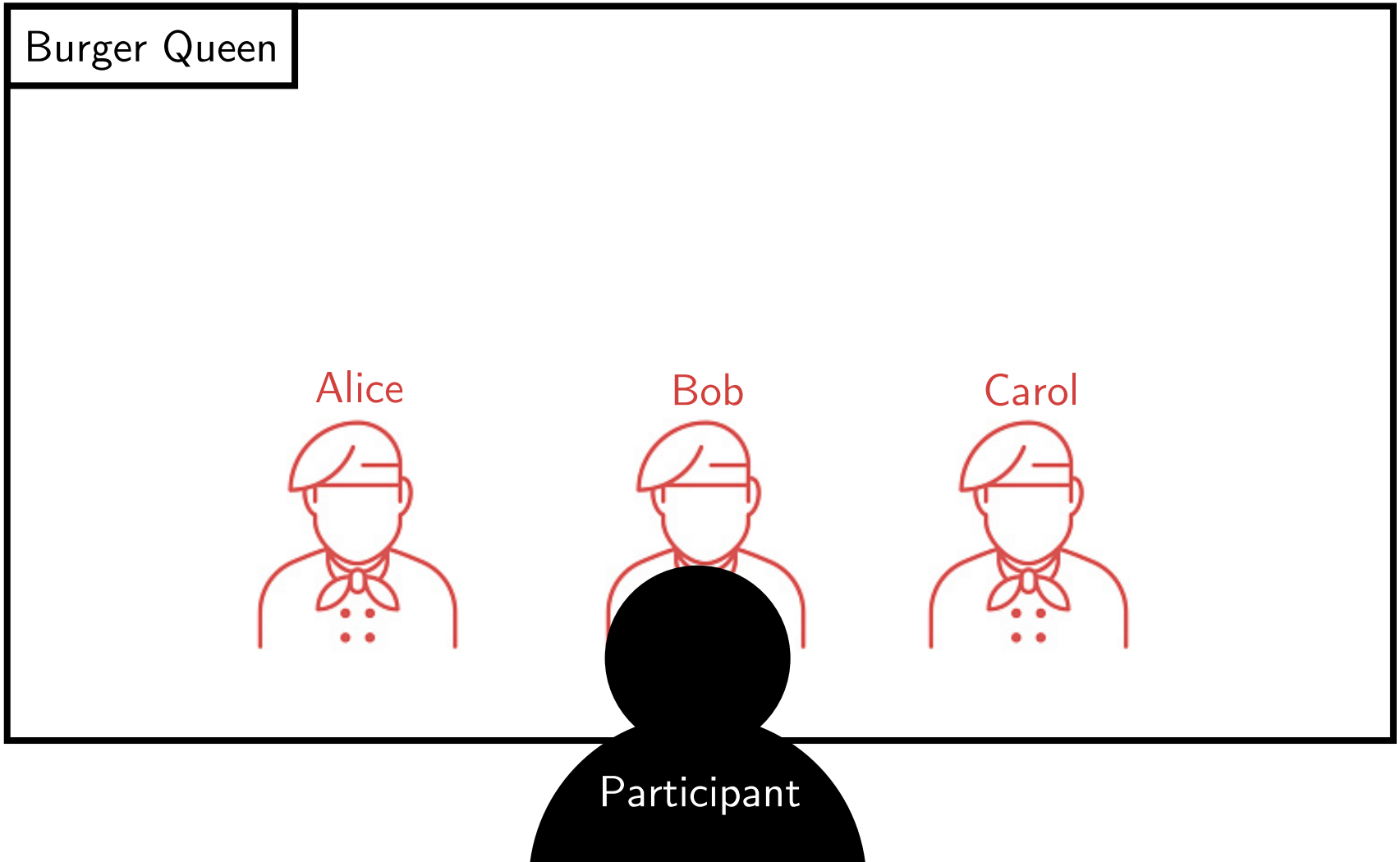
Wharton Behavioral Lab

N = 203

Queueing Game



Queueing Game

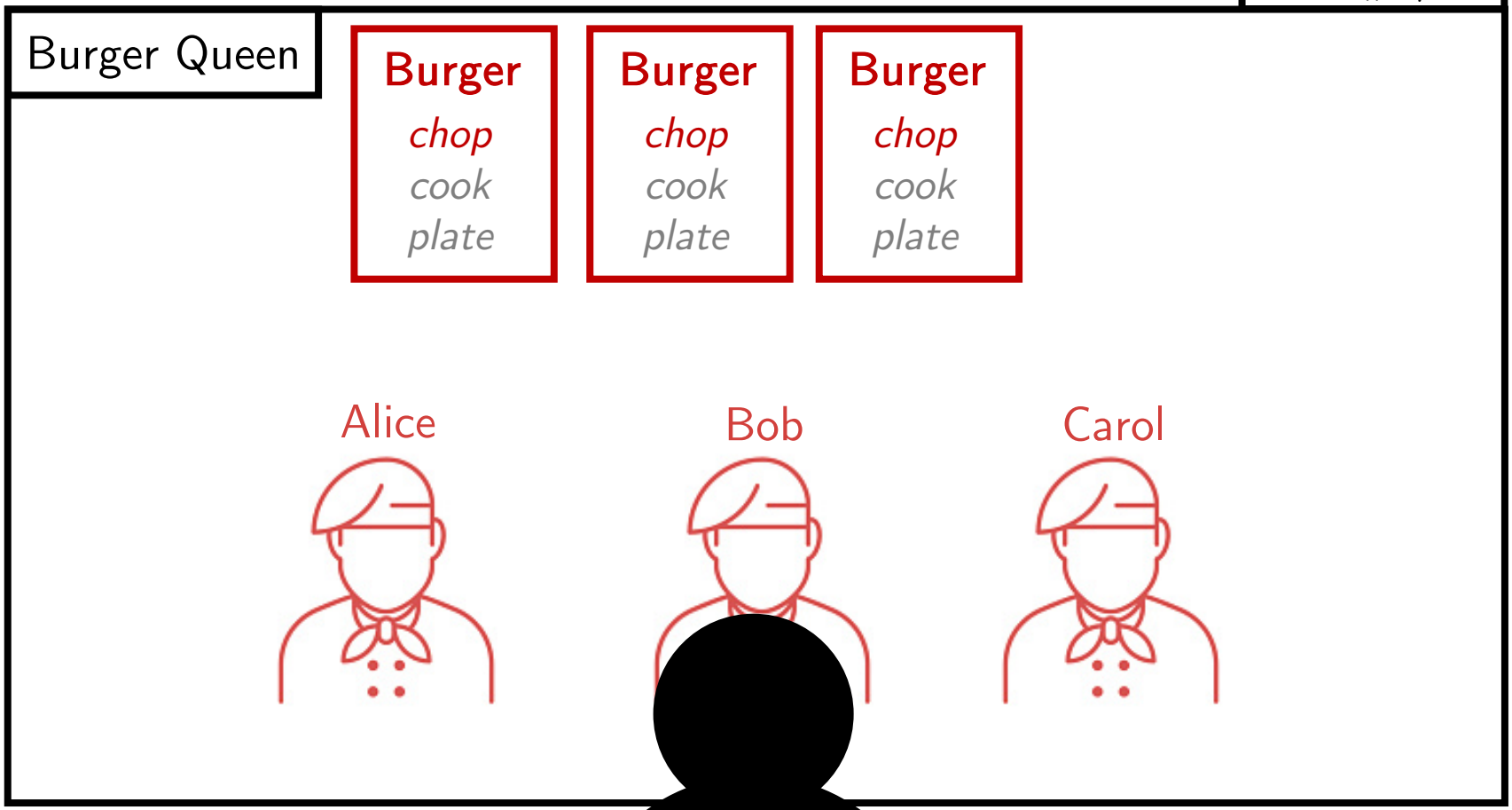


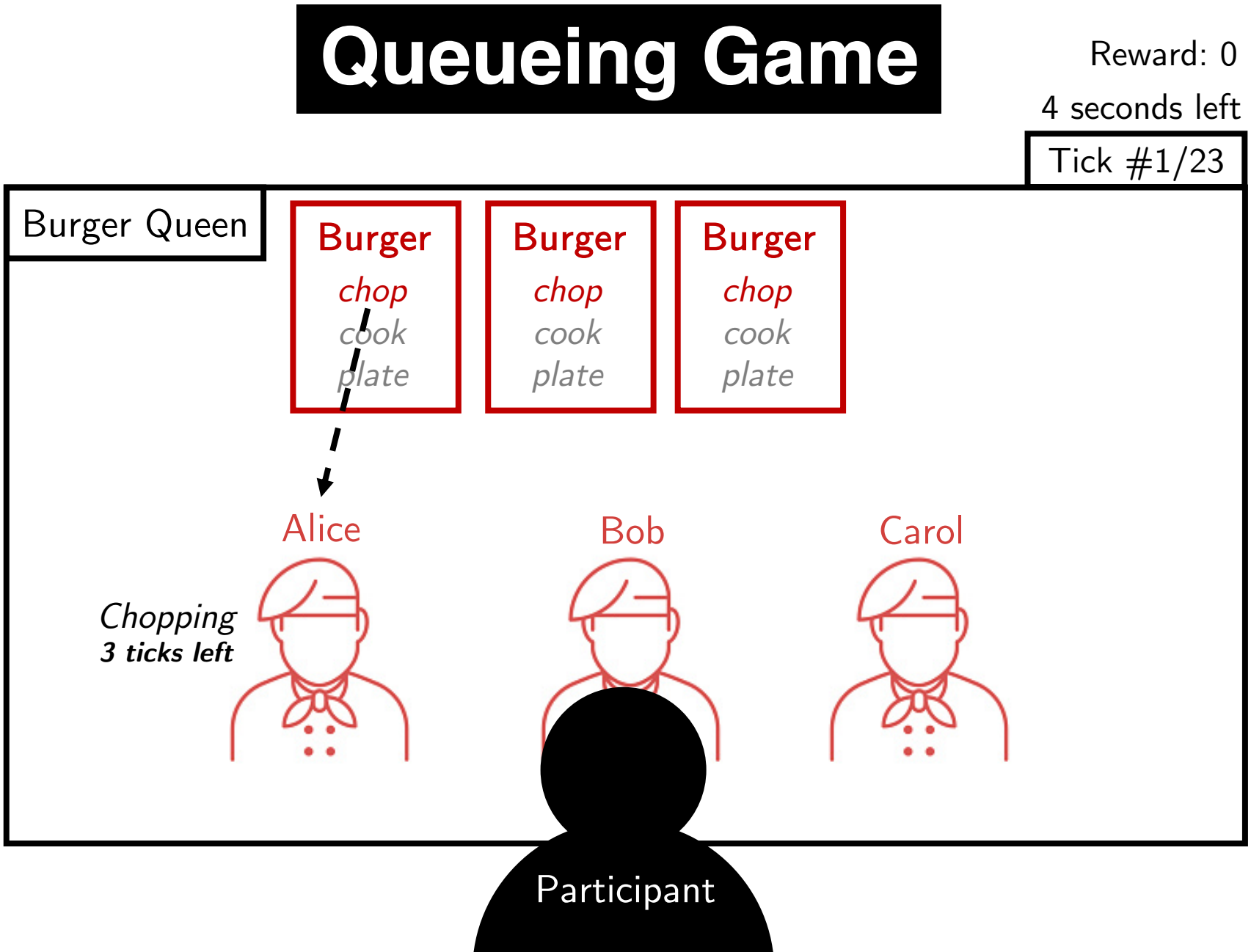
Queueing Game

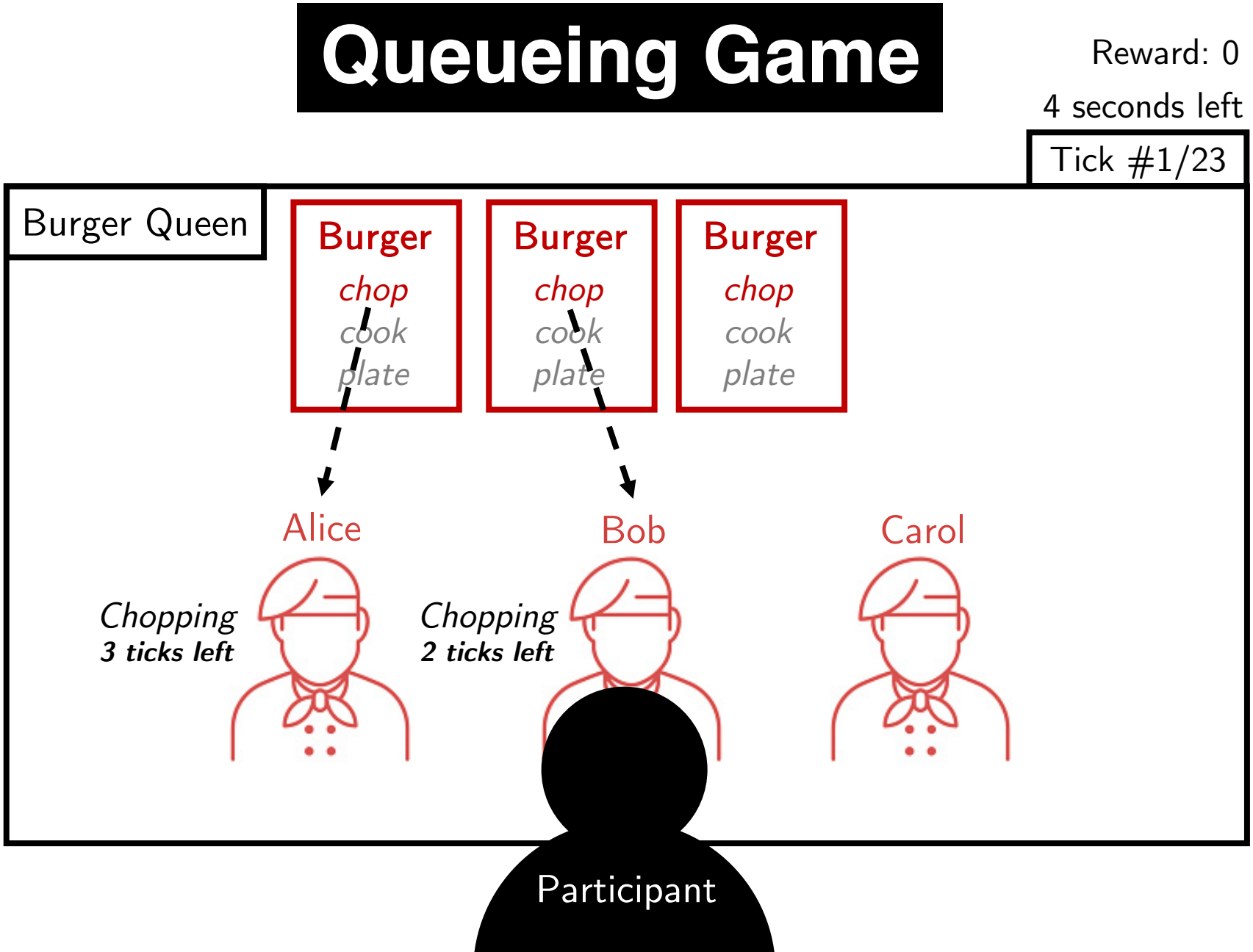
Reward: 0

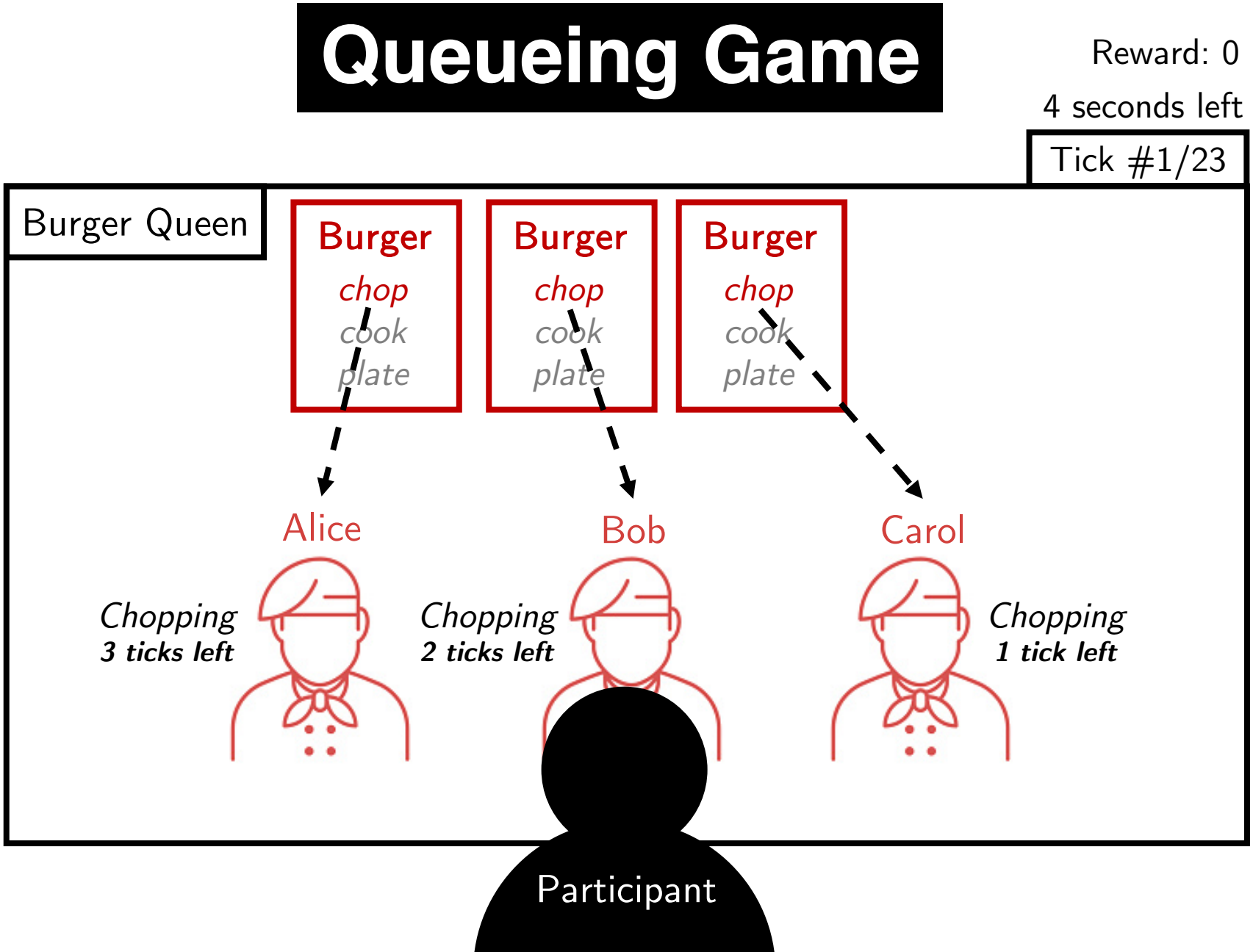
4 seconds left

Tick #1/23

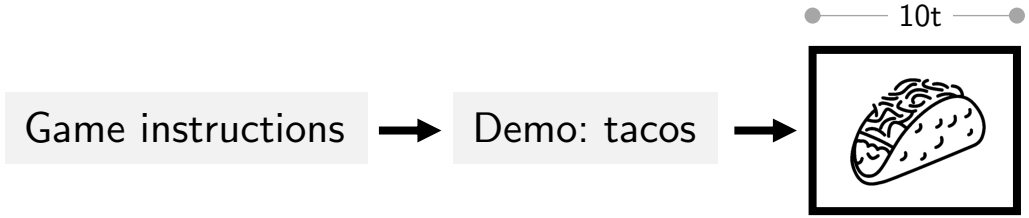



Queueing Game
Reward: 0
4 seconds left
Tick #1/23
Burger Queen
Burger
chop
cook
plate
Burger
chop
cook
plate
Burger
chop
cook
plate
Alice
Bob
Carol
Chopping
3 ticks left
Participant

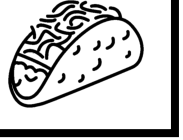

Queueing Game
Reward: 0
4 seconds left
Tick #1/23
Burger Queen
Burger
chop
cook
plate
Burger
chop
cook
plate
Burger
chop
cook
plate
Alice
Bob
Carol
Chopping
3 ticks left
Chopping
2 ticks left
Participant

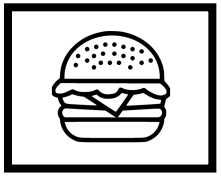

Queueing Game
Reward: 0
4 seconds left
Tick #1/23
Burger Queen
Burger
chop
cook
plate
Burger
chop
cook
plate
Burger
chop
cook
plate
Alice
Bob
Carol
Chopping
3 ticks left
Chopping
2 ticks left
Chopping
1 tick left
Participant

Experiment Flow

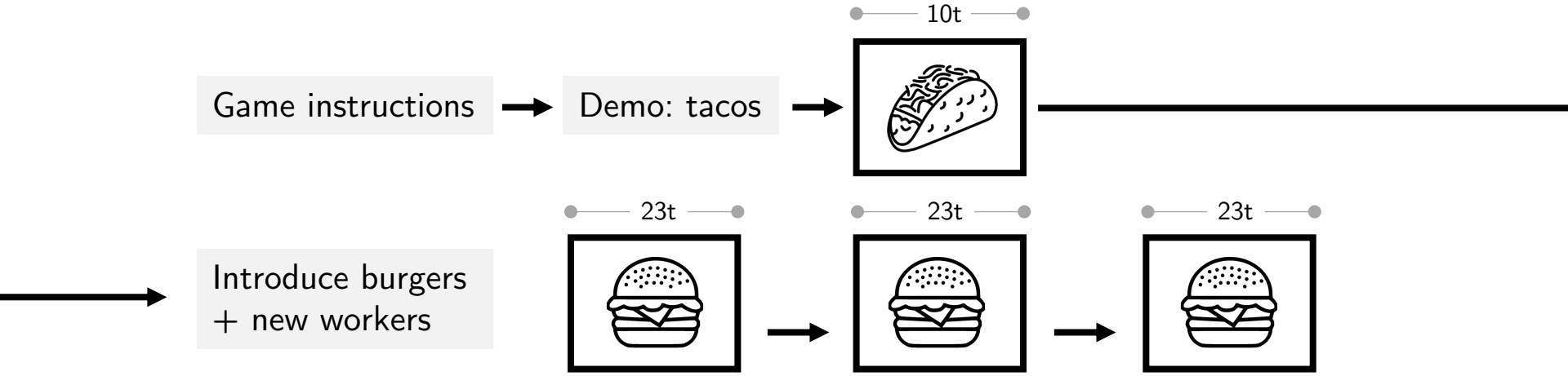


Experiment Flow

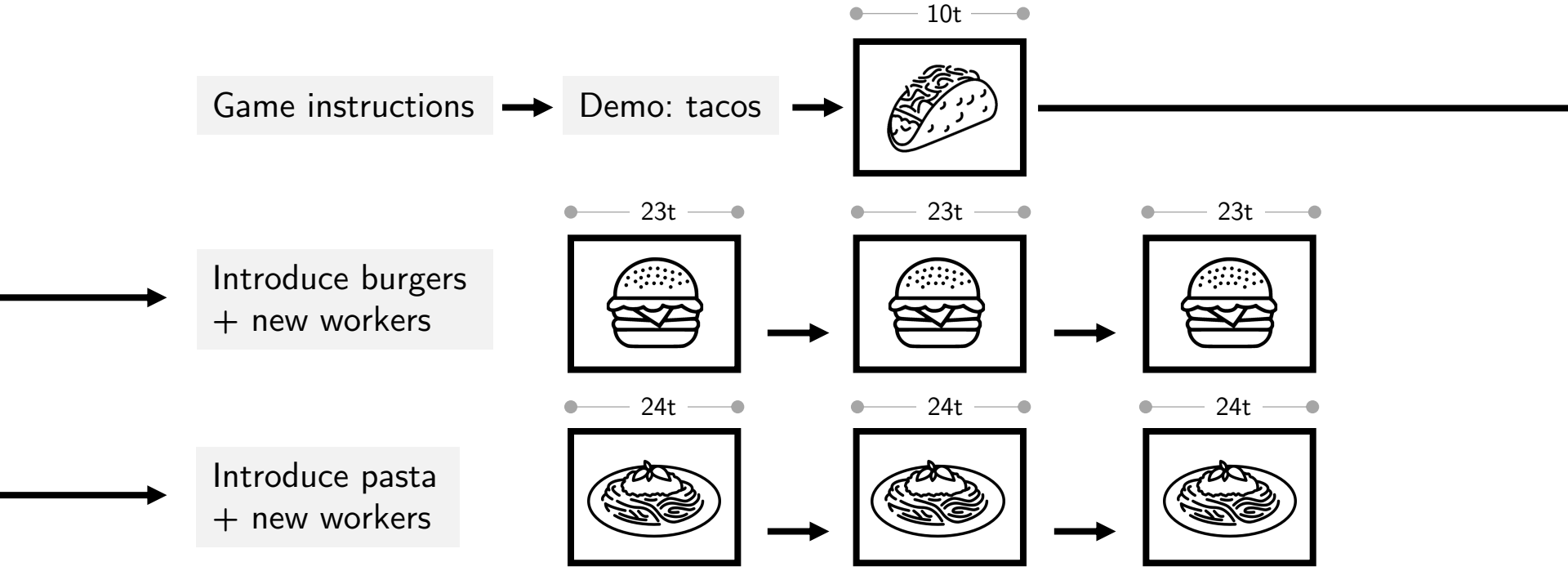
Game instructions → Demo: tacos → 10t 

→ Introduce burgers + new workers → 23t 

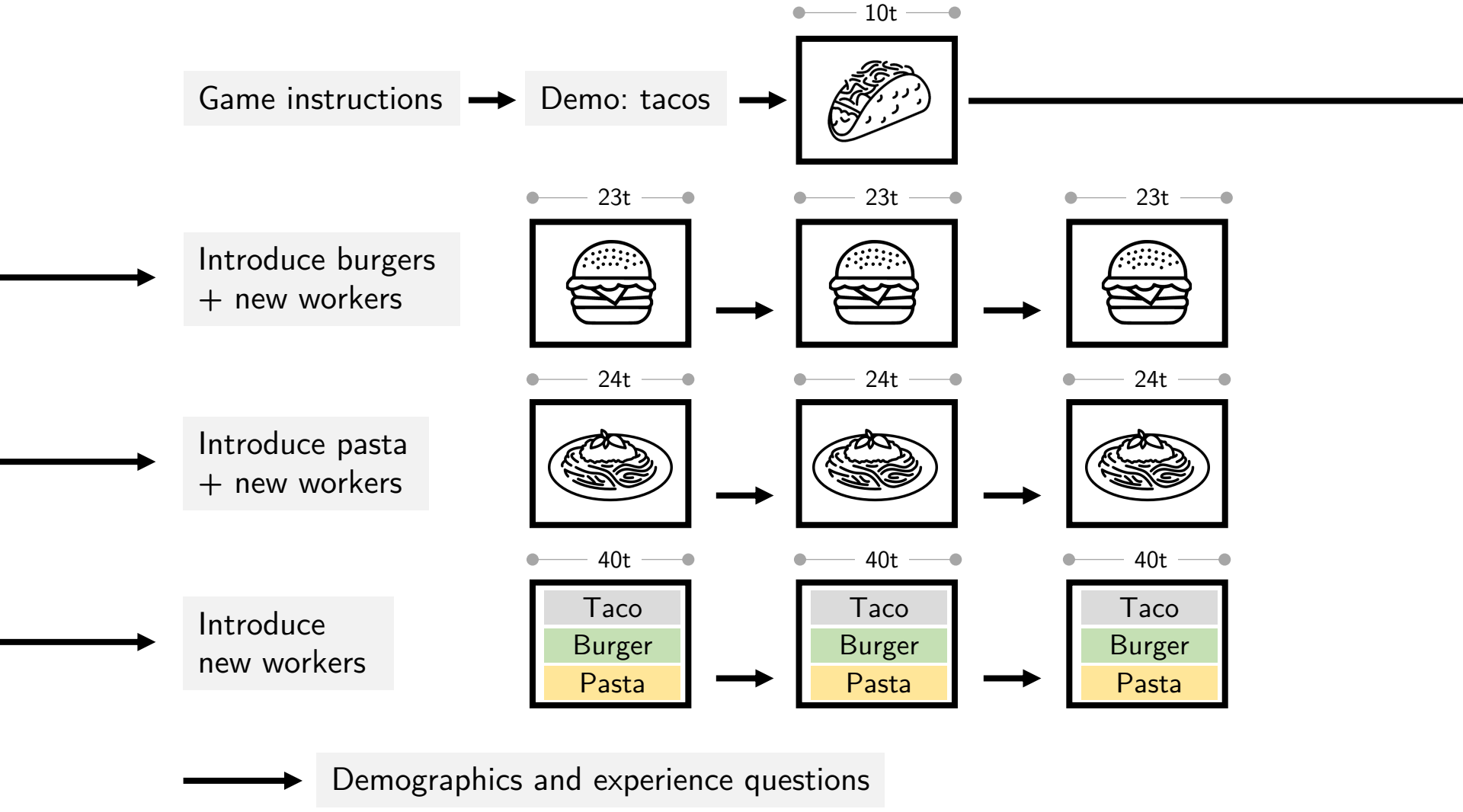
Experiment Flow



Experiment Flow



Experiment Flow



Experiment Learning Workers' Skills

Experiment Learning Workers' Skills

Role:	Server	Sous-Chef	Chef

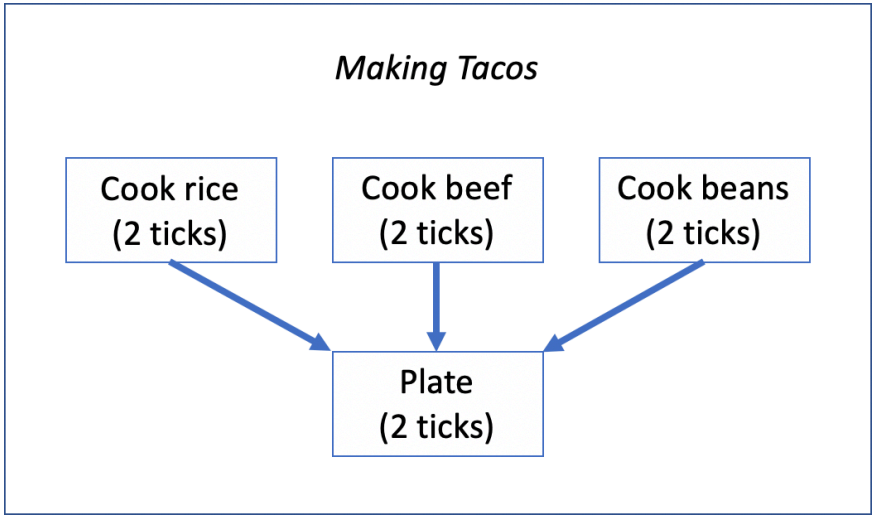
Unknown to participants

Experiment Learning Workers' Skills

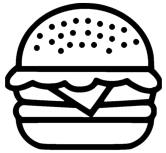
Role:	Server	Sous-Chef	Chef
Chopping:	Slow	Fast	Fast
Cooking:	Slow	Medium	Fast
Plating:	Fast	Medium	Slow

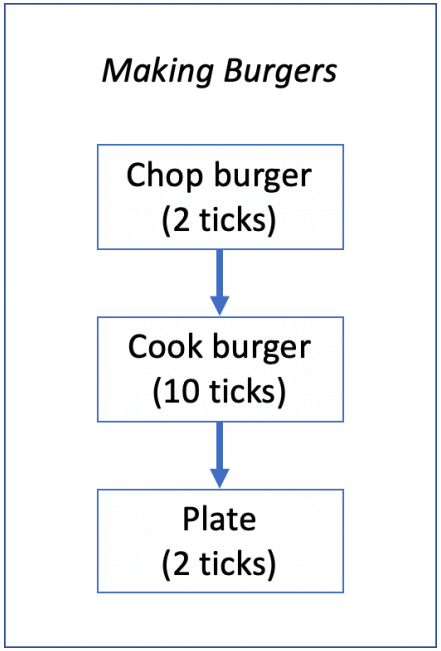
Unknown to participants

Experiment Learning Tasks



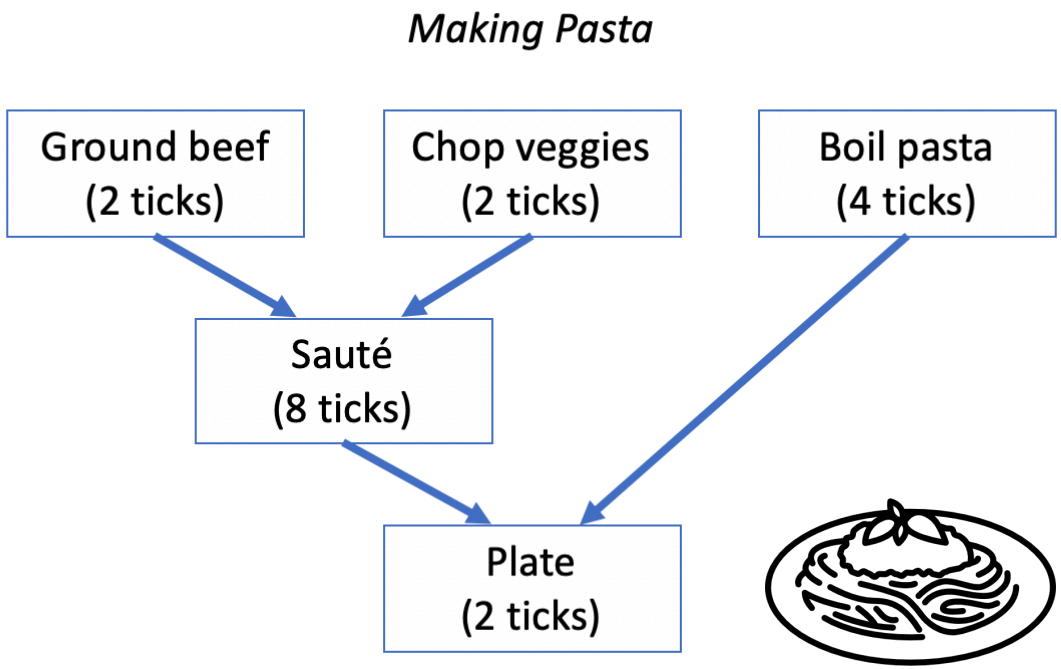
Parallel Tasks





Sequential Tasks

Experiment Learning Tasks



Hybrid Tasks (Both Parallel and Sequential)

Experiment Handcrafted Tips

Control

No tips.

Tips

Experiment Handcrafted Tips

Control

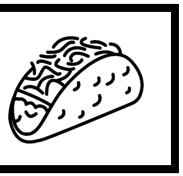
No tips.

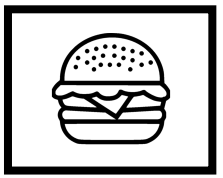
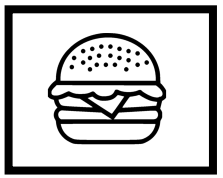
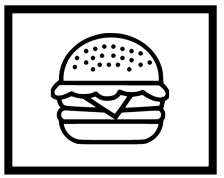
Tips

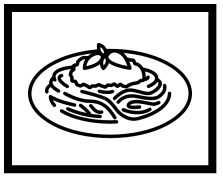
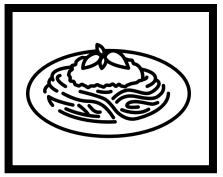
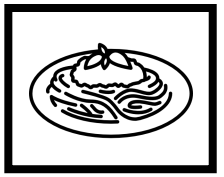
"Prioritize cooking and chopping tasks for Bob and Carol, and plating tasks for Alice."

"...Carol should NEVER plate, and Alice should NEVER cook (it's better to leave them idle than to give them these tasks.)"

Experiment Flow

Game instructions → Demo: tacos → 10t 

Introduce burgers + new workers → 23t  Tips → 23t  Tips → 23t 

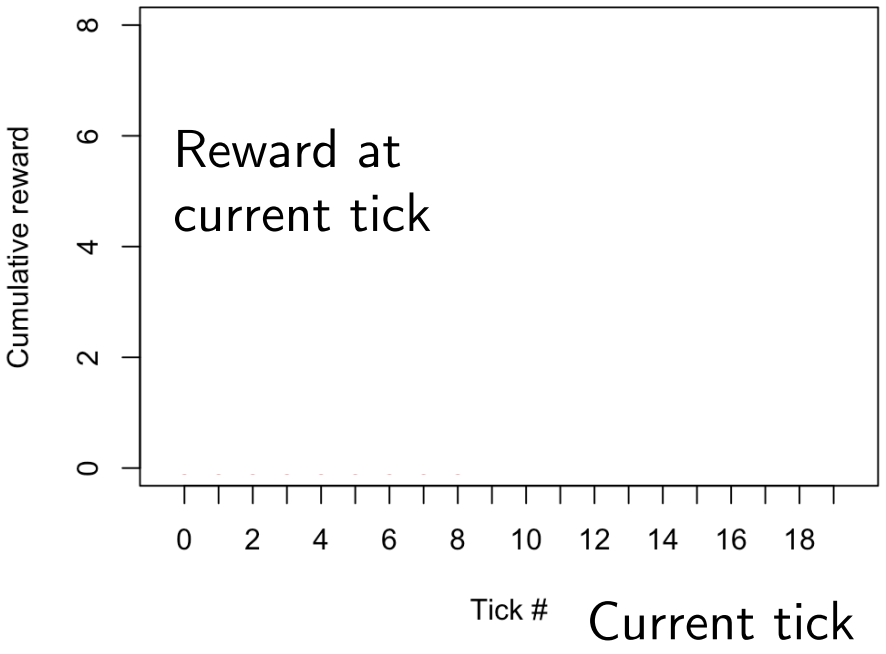
Introduce pasta + new workers → 24t  Tips → 24t  Tips → 24t 

Introduce new workers → 40t Taco / Burger / Pasta Tips → 40t Taco / Burger / Pasta Tips → 40t Taco / Burger / Pasta

Demographics and experience questions

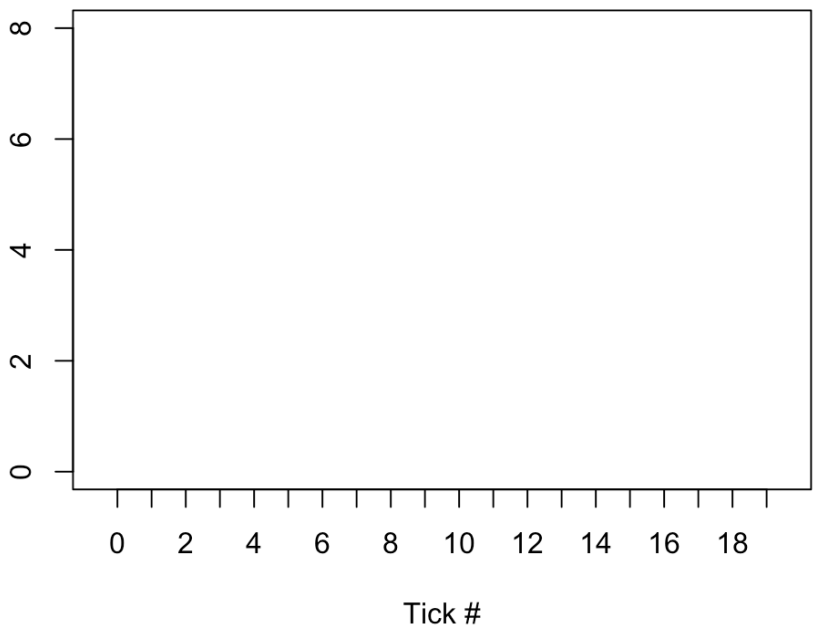
Results Performance

Burger Round 1

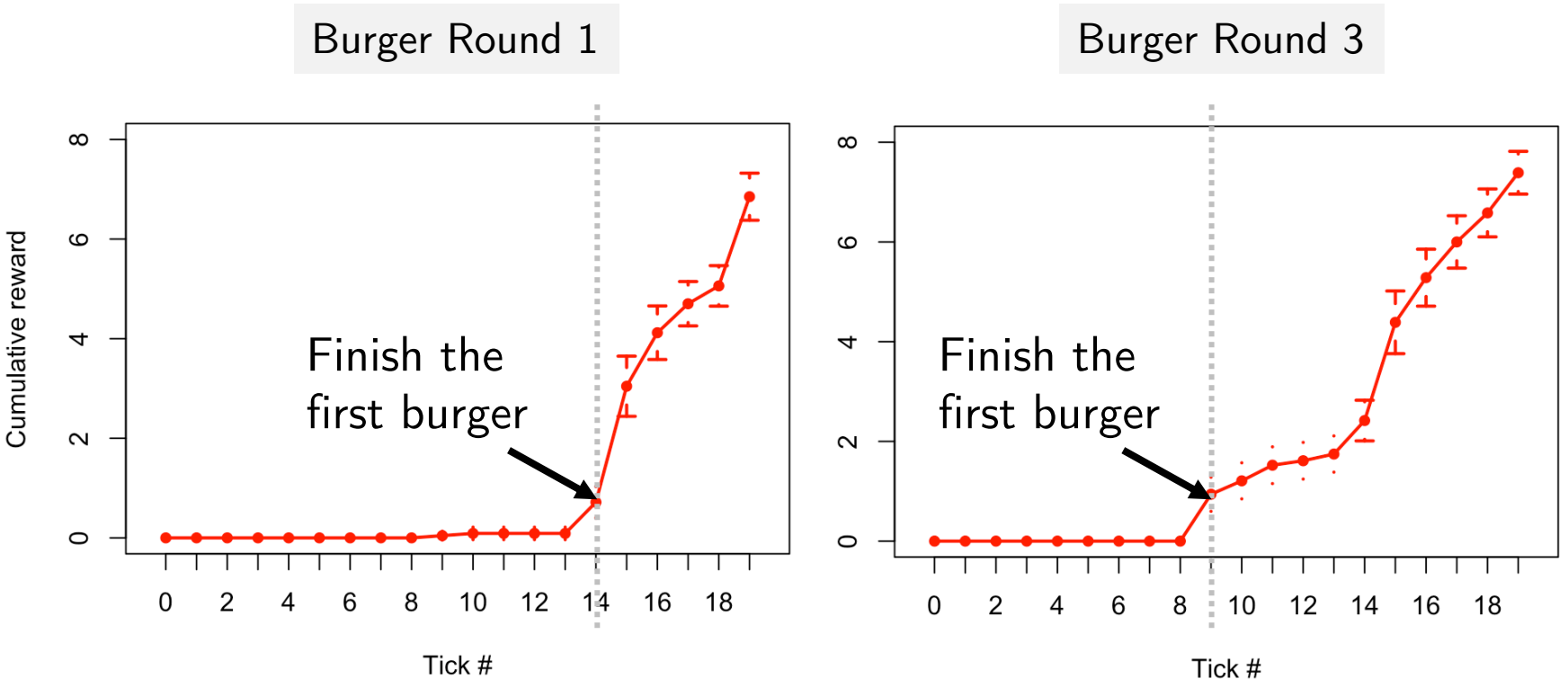


Current tick

Burger Round 3



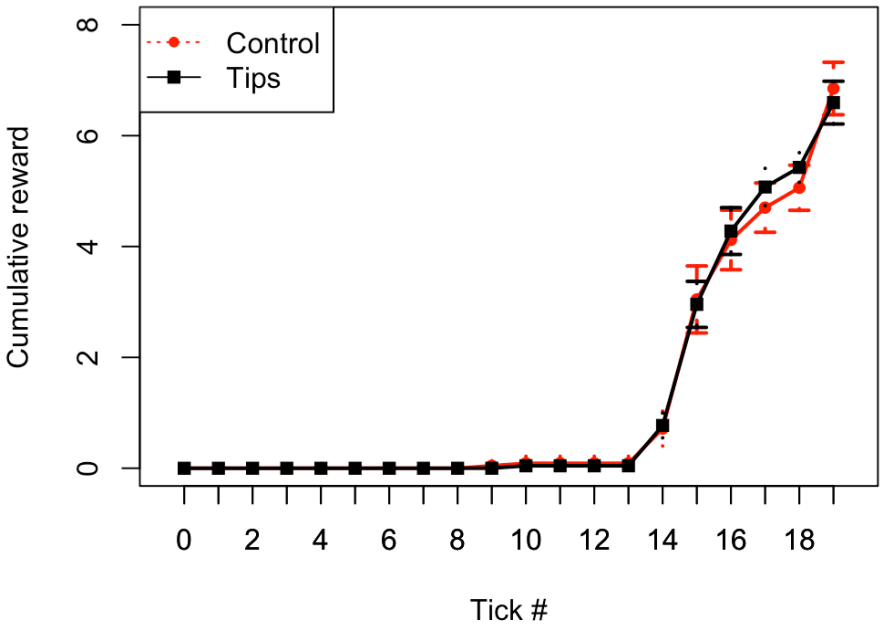
Results Performance



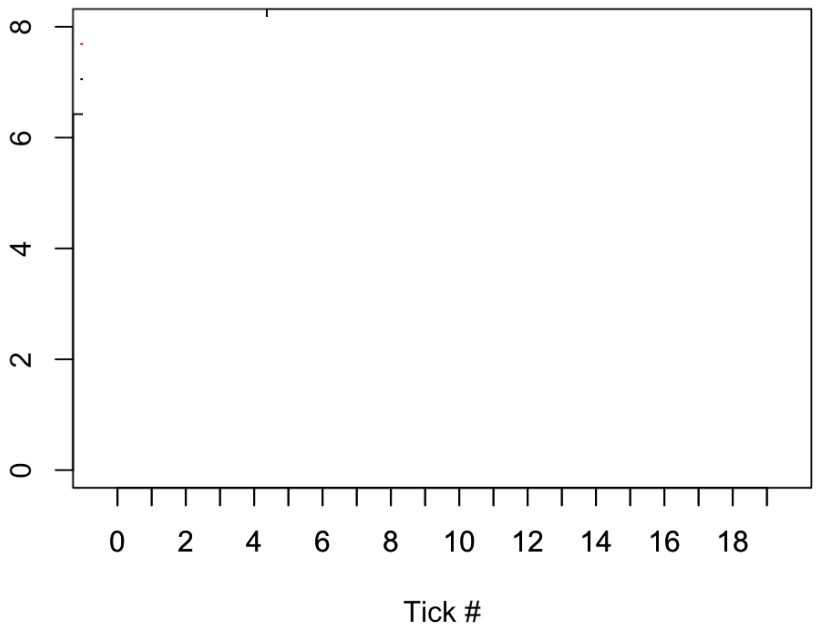
Control: Over time, people improve.

Results

Burger Round 1

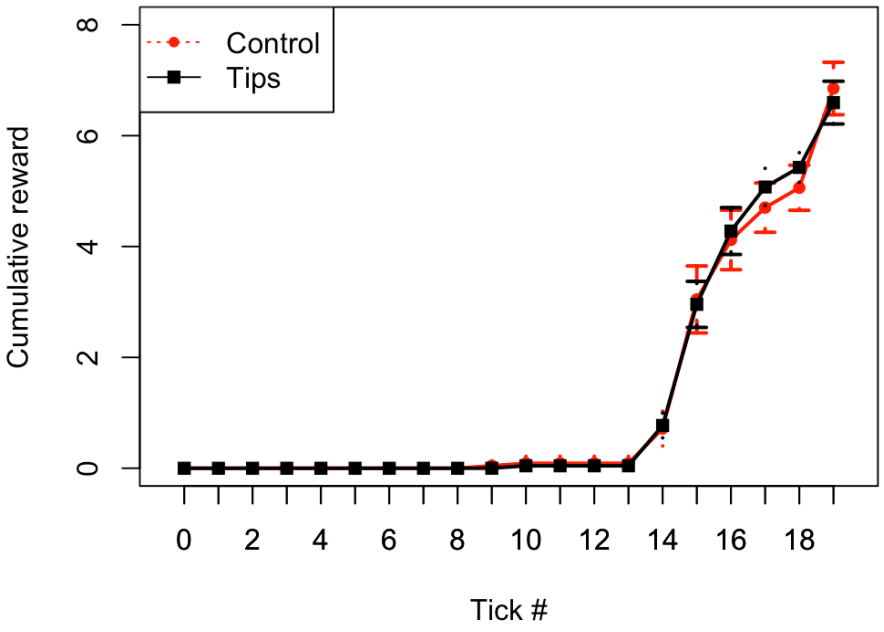


Burger Round 3

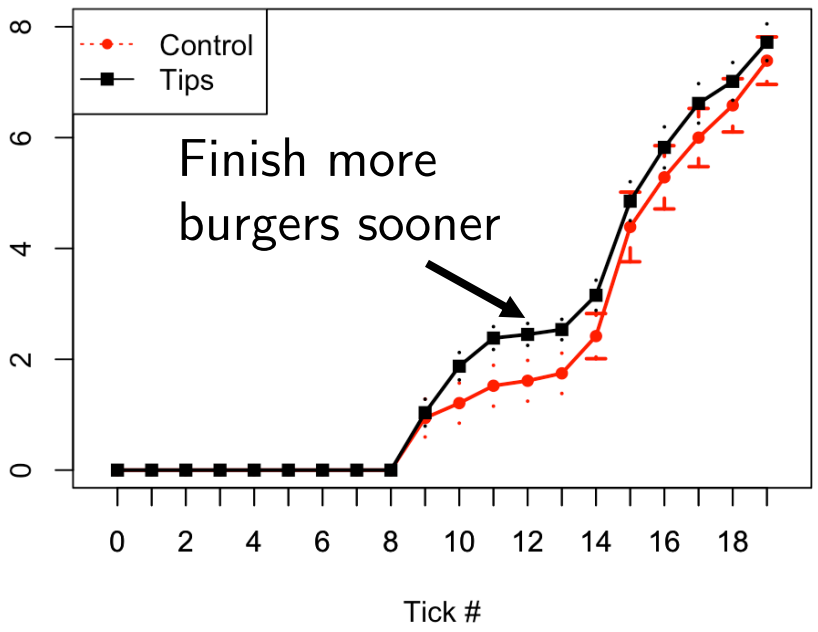


Results Tips Help

Burger Round 1



Burger Round 3



With Tips: Higher score, improve faster

Results Tips Help

Suboptimal Decisions e.g., assigning high-skilled chef to plate a dish

%	Burger #1	#2	#3	Pasta #1	#2	#3
Control	5.49	3.88	3.31	3.26	2.81	2.54
Tips	2.78	1.53	1.30	1.38	1.16	0.84

With Tips: Higher score, improve faster, make fewer suboptimal decisions

Results Tips Help

Suboptimal Decisions e.g., assigning high-skilled chef to plate a dish

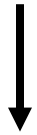
%	Burger #1	#2	#3	Pasta #1	#2	#3
Control	5.49	3.88	3.31	3.26	2.81	2.54
Tips	2.78	1.53	1.30	1.38	1.16	0.84

With Tips: Higher score, improve faster, make fewer suboptimal decisions

In our setting, people can potentially improve ✓

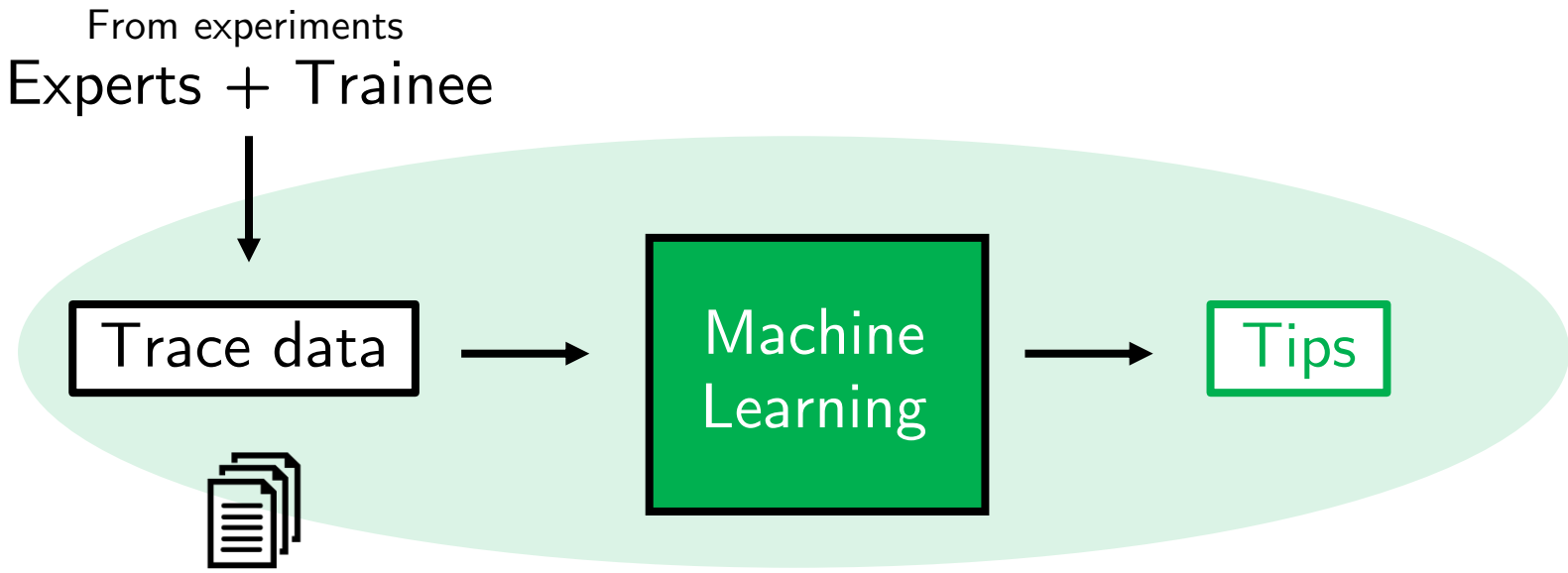
From experiments

Experts + Trainee

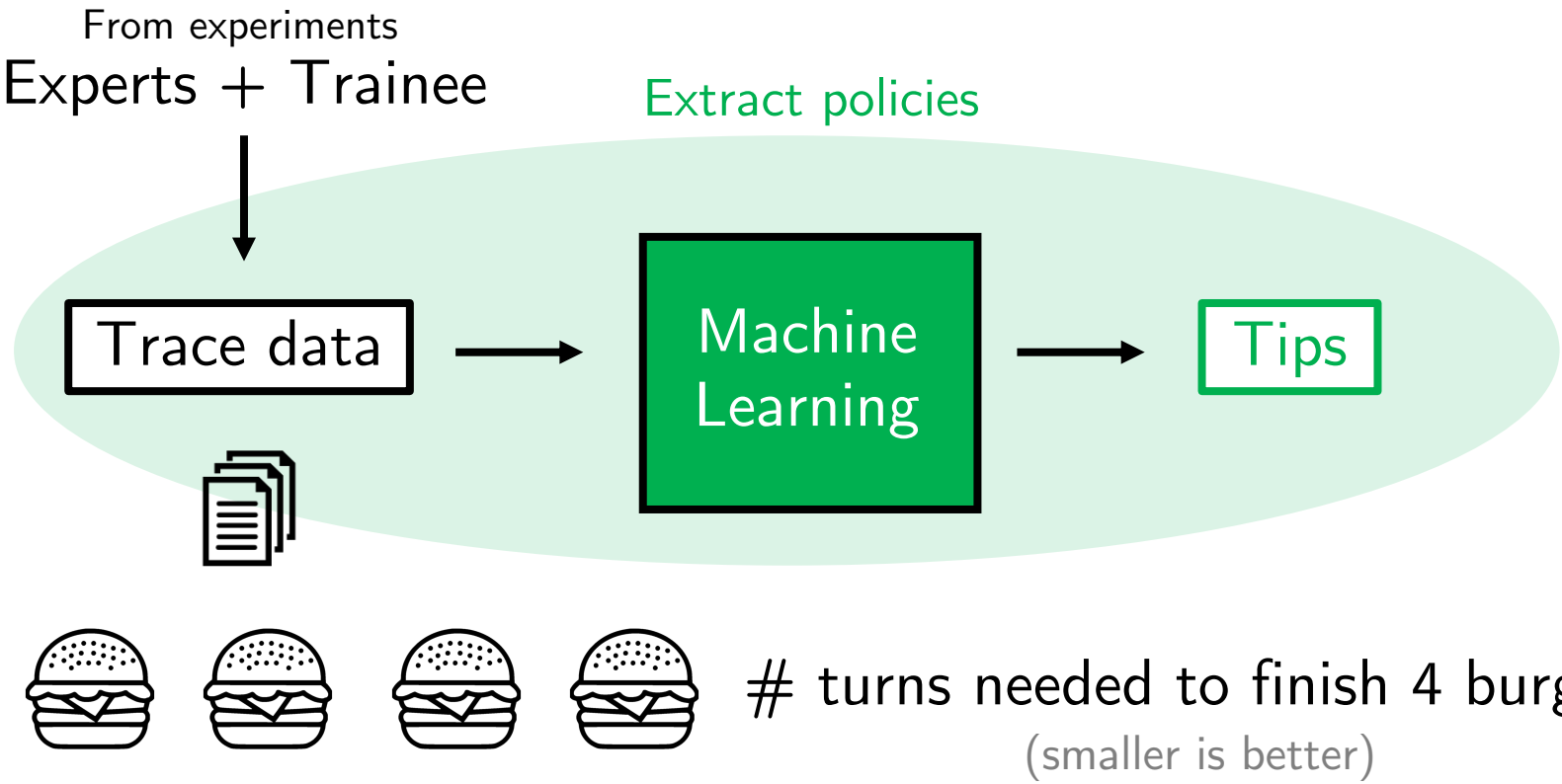


Trace data

Testing Our Framework



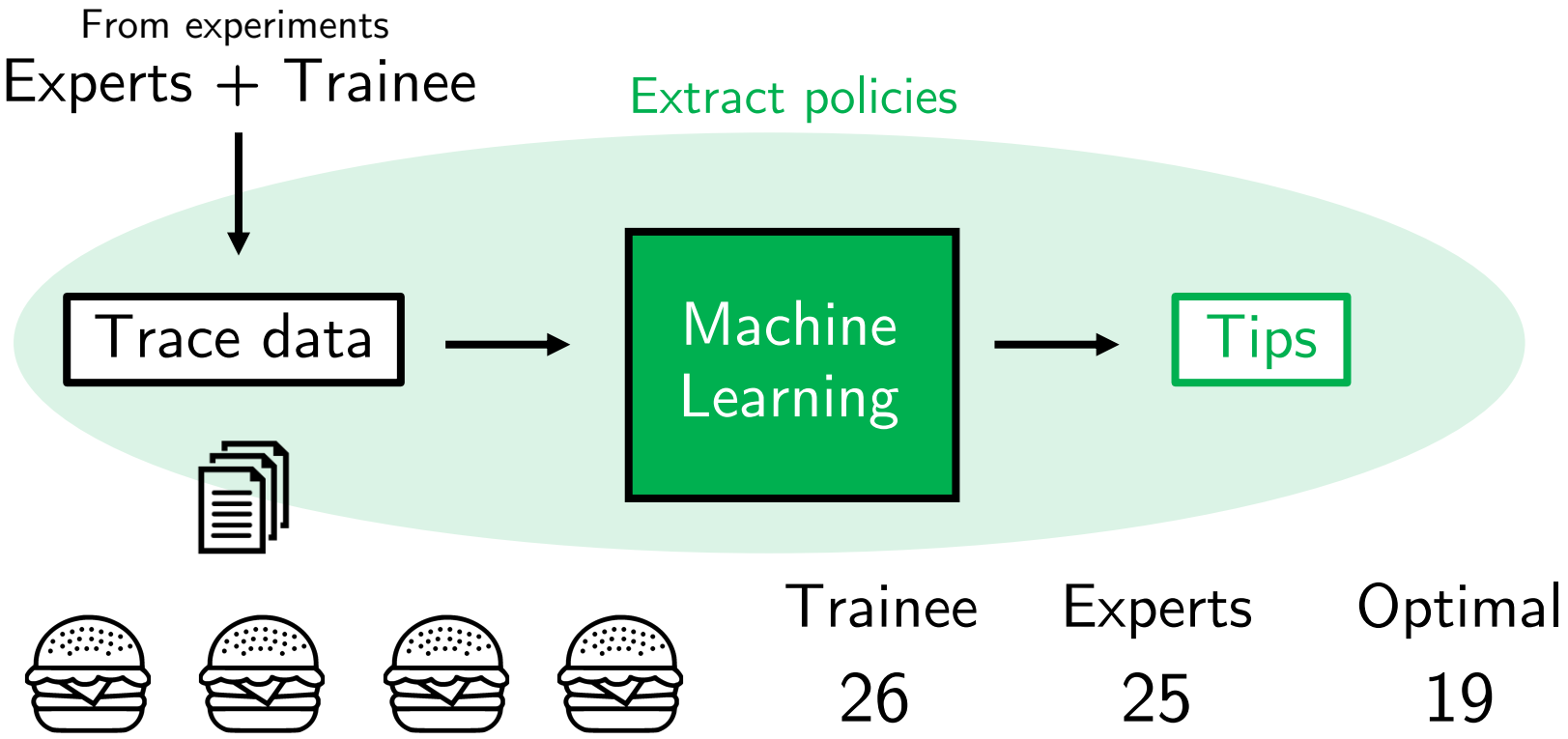
Testing Our Framework



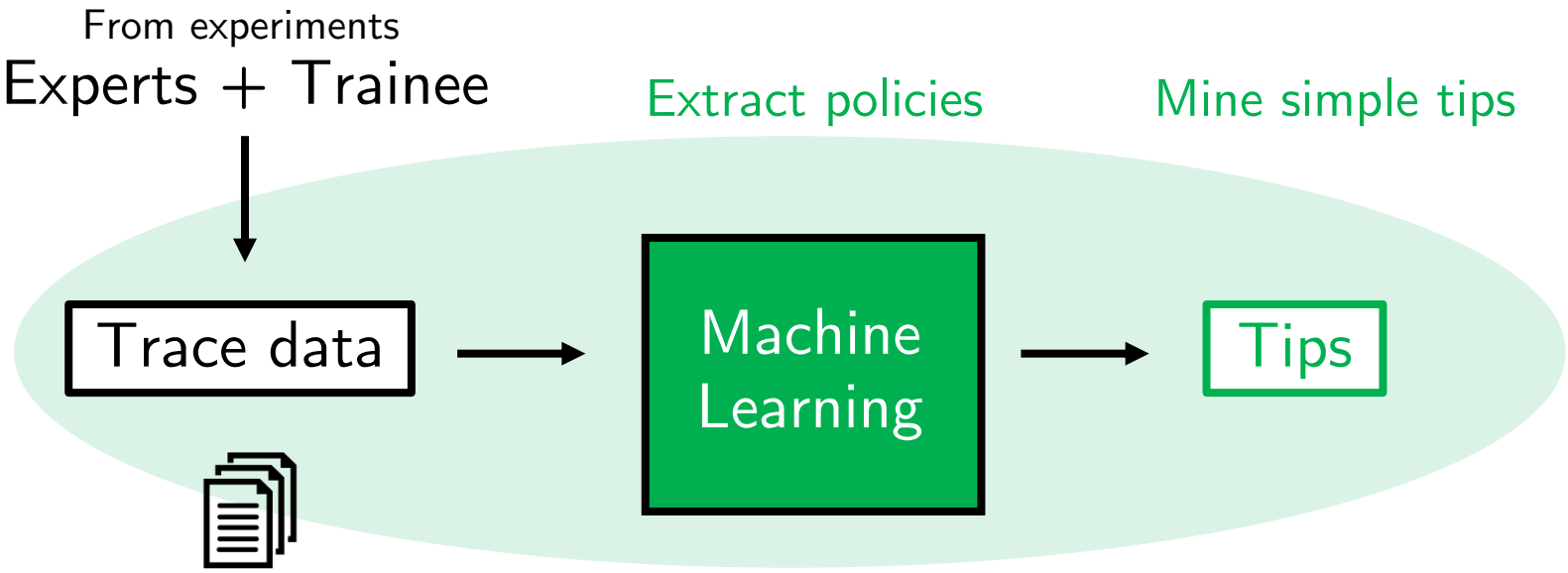
turns needed to finish 4 burgers

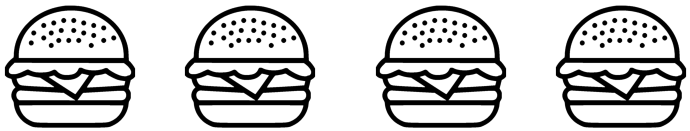
(smaller is better)

Testing Our Framework



Testing Our Framework





Trainee	Experts	Optimal
26	25	19

	Available Workers	Open Tasks	Action	Best Perf/Freq
1	Everyone	Cooking	Leave server idle	**19** / 19%

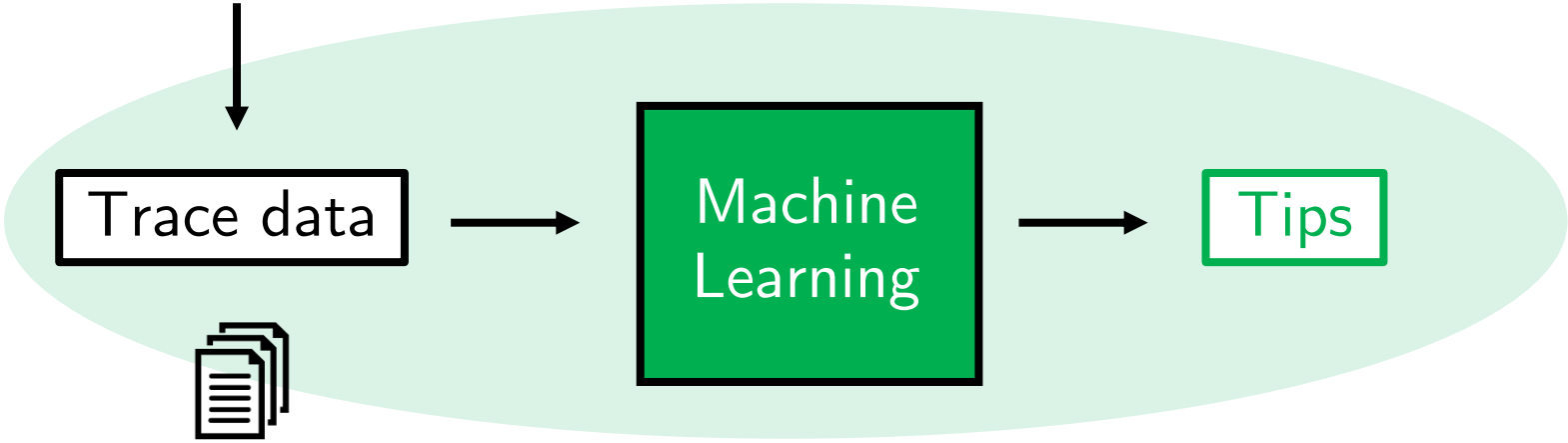
Testing Our Framework

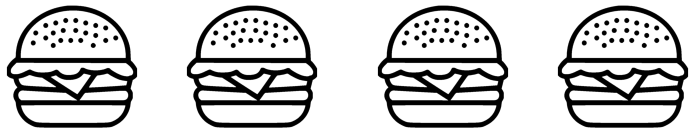
From experiments

Experts + Trainee

Extract policies

Mine simple tips

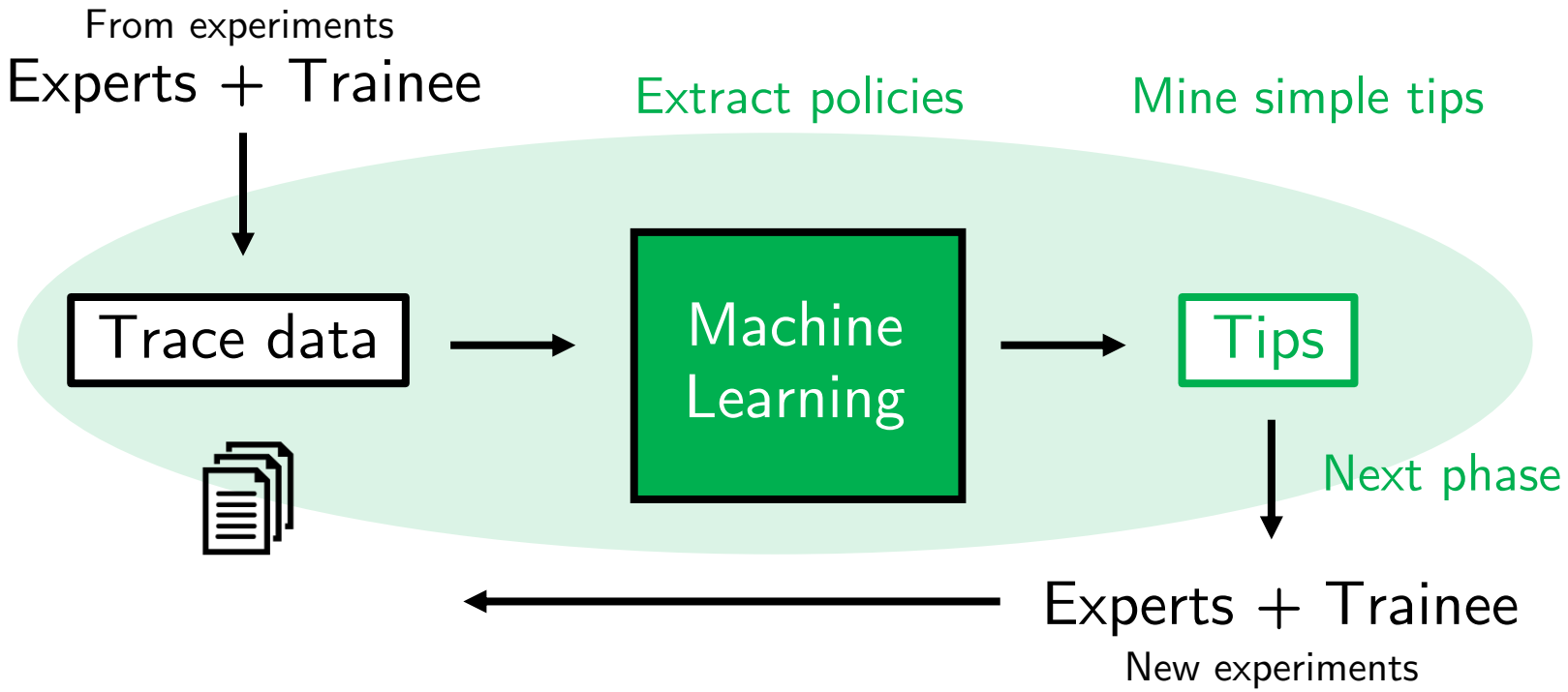




Trainee	Experts	Optimal
26	25	19

Available Workers	Open Tasks	Action	Best Perf/Freq
2 Chef + Server	Plating	Leave chef idle	19 / 4%

Testing Our Framework

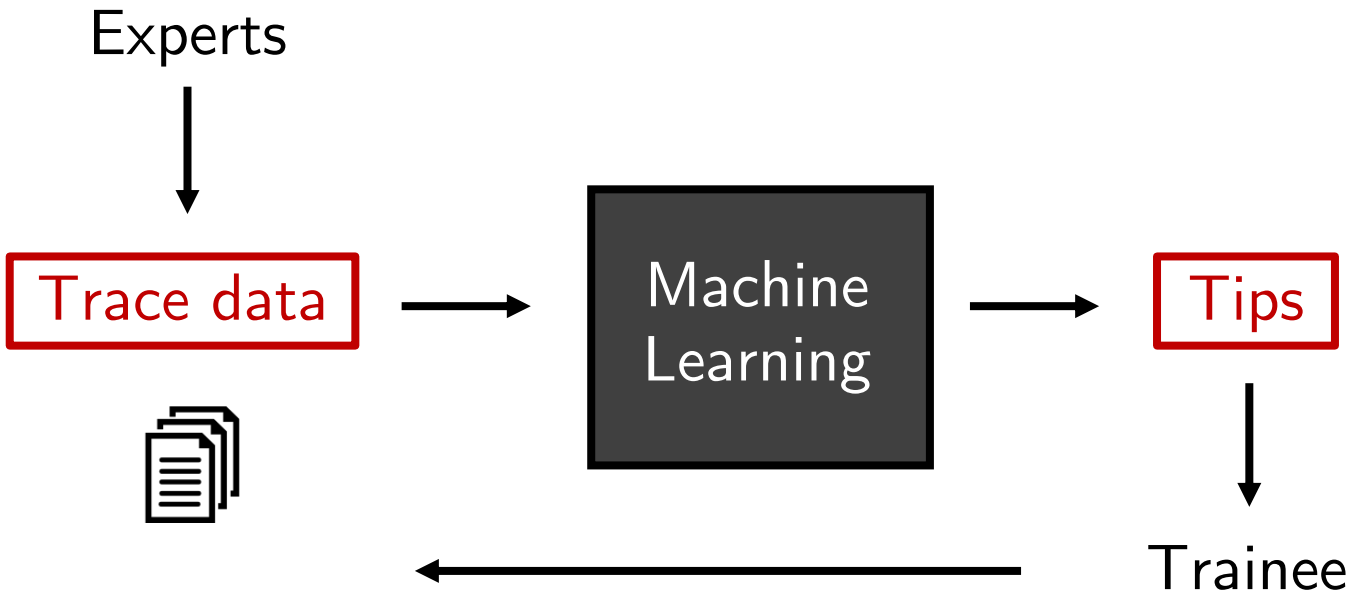


On-Going Work

- Implement personalized tips in the next phase of experiments, dynamically choosing tips
- Improve tips learning algorithms
  - Can use imitation learning as well
  - Fit a model predicting when (s, π^*(a*)) differ (s, π^*(a))
- Extend to team collaboration

Summary

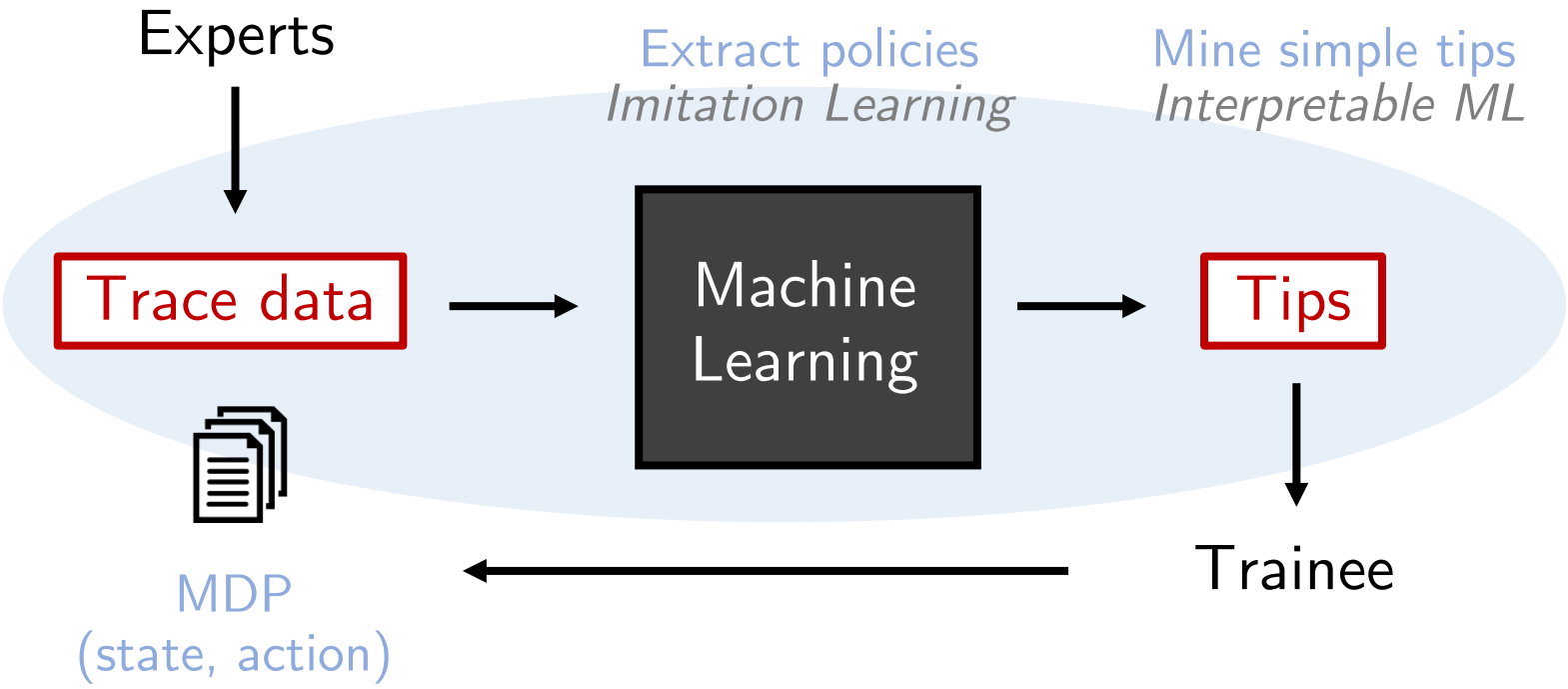
ML to automatically help people improve in a personalized and dynamic way



Hamsa Bastani, Osbert Bastani, **Park Sinchaisri** (swich@wharton.upenn.edu | @wichinpong)

Summary

ML to automatically help people improve in a personalized and dynamic way

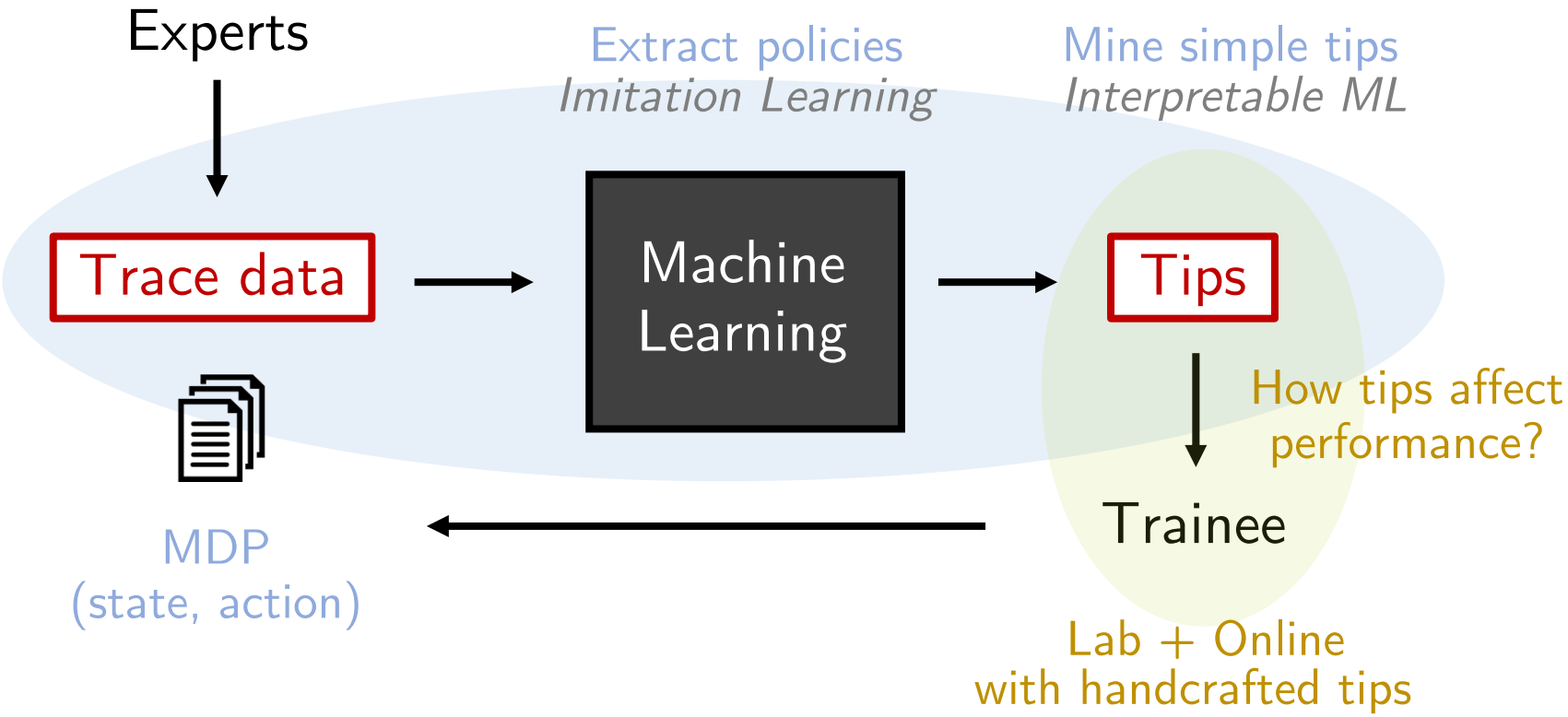


Today: Framework

Hamsa Bastani, Osbert Bastani, **Park Sinchaisri** (swich@wharton.upenn.edu | @wichinpong)

Summary

ML to automatically help people improve in a personalized and dynamic way

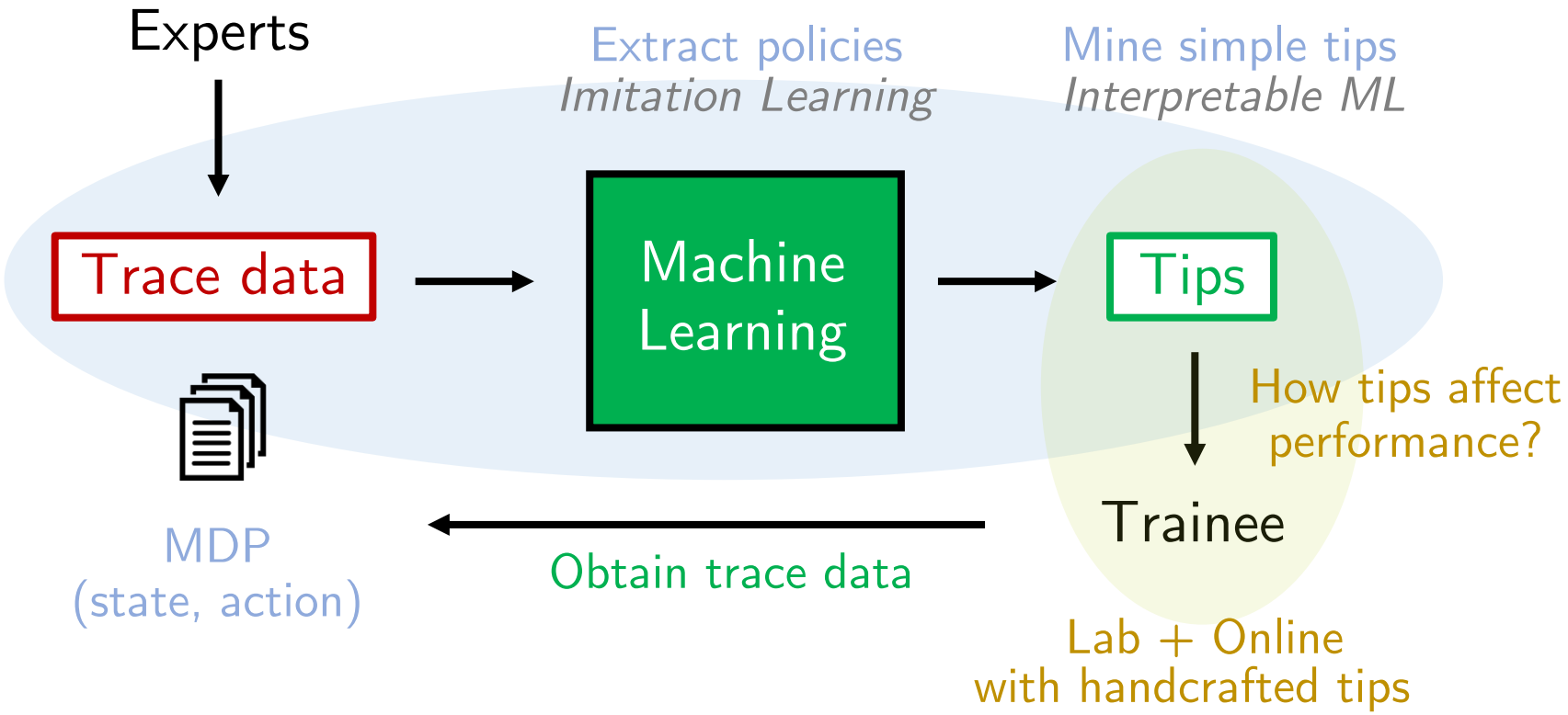


Today: Framework | Pilot Experiments

Hamsa Bastani, Osbert Bastani, **Park Sinchaisri** (swich@wharton.upenn.edu | @wichinpong)

Summary

ML to automatically help people improve in a personalized and dynamic way



Today: Framework | Pilot Experiments | Policies + Tips

Hamsa Bastani, Osbert Bastani, **Park Sinchaisri** (swich@wharton.upenn.edu | @wichinpong)

Policy Gradient

Recall that we are given a Markov Decision Process (S, A, P, R) denoting states, actions, transition probabilities, and rewards respectively. We seek an optimal policy $\pi^* : S \to A$ over a horizon of T time steps and a discount factor γ. In order to perform gradient descent, we will featurize all quantities of interest, so that we can parametrize π ny some θ.

We start by defining the value function:

$$V^{(\theta)}(s) = R(s) + \gamma \sum_{s' \in S} \sum_{a \in A} \pi(a|s) \cdot P(s'|s, a) \cdot V^{(\theta)}(s') \,.$$

The cost-to-go function is then

$$J(\theta) = \mathbb{E}_{\substack{s \sim D^{(\pi)} \\ a \sim \pi(\cdot|s)}} V^{(\theta)}(s) \,.$$

Sometimes it is easier to work with the Q-function:

$$Q^{(\theta)}(s, a) = R(s) + \gamma \sum_{s' \in S} P(s'|s, a) \cdot V^{(\theta)}(s') \,.$$

We wish to optimize $J(\theta)$ as a function of our policy using gradient descent techniques. Therefore, we require the *policy gradient*:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\substack{s \sim D^{(\pi)} \\ a \sim \pi(\cdot|s)}} \left[Q^{(\theta)}(s, a) \cdot \nabla_\theta \log \pi_\theta(a|s) \,. \right]$$

Policy Gradient

However, we clearly do not know the Q-function, so we cannot directly compute this gradient. Instead, we will estimate it using the following simple procedure:

1. Sample N rollouts using π_θ, *i.e.*,

$$\zeta = (s_0, a_0, r_0, s_1, a_1, r_1, \cdots s_{T-1}, a_{T-1}, r_{T-1}) .$$

2. Estimate the Q-function as

$$\hat{Q}_t = \sum_{t'=t}^{T-1} \gamma^{t'-t} \cdot \tilde{r}_{t'} ,$$

where $\tilde{r}_t$ are normalized rewards, *i.e.*, $\tilde{r}_t = \frac{r_t - \mu}{\sigma}$, where μ and σ are the average and standard deviation of the rewards from the most recent N rollouts.

3. Estimate the policy gradient

$$\nabla_\theta J(\theta) \approx \sum_{t=0}^{T-1} \hat{Q}_t \cdot \nabla_\theta \log \pi_\theta(a_t|s_t) .$$

The above is for a single rollout. It is recommended to average this quantity over all N rollouts.

Feeding a randomly chosen initial policy as well as the gradient computation procedure above to an optimizer like ADAM in Pytorch should yield an estimated optimal policy.