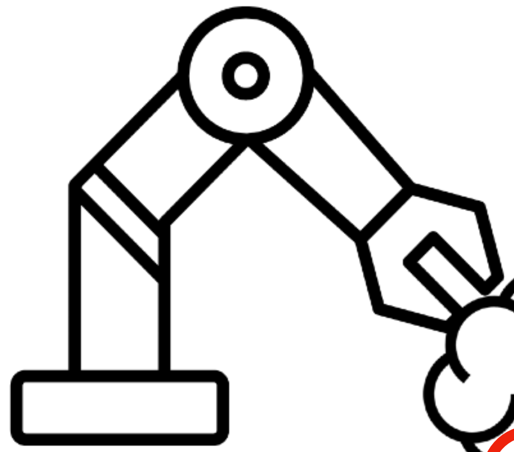
Estimating and penalizing preference shifts induced by recommender systems

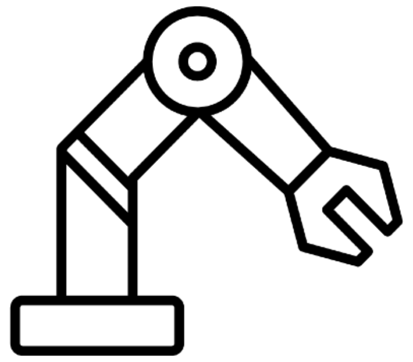
Micah Carroll, Dylan Hadfield-Menell, Stuart Russell, Anca Dragan

Preference influence? Preliminaries

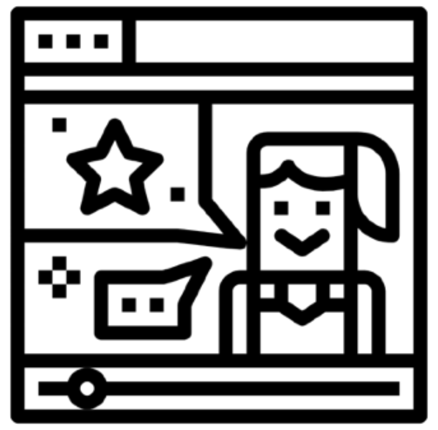


- Behavior on the platform
- User’s psychological state
- Polarization? Fake news / conspiracy content?
- Preferences?

User dynamics

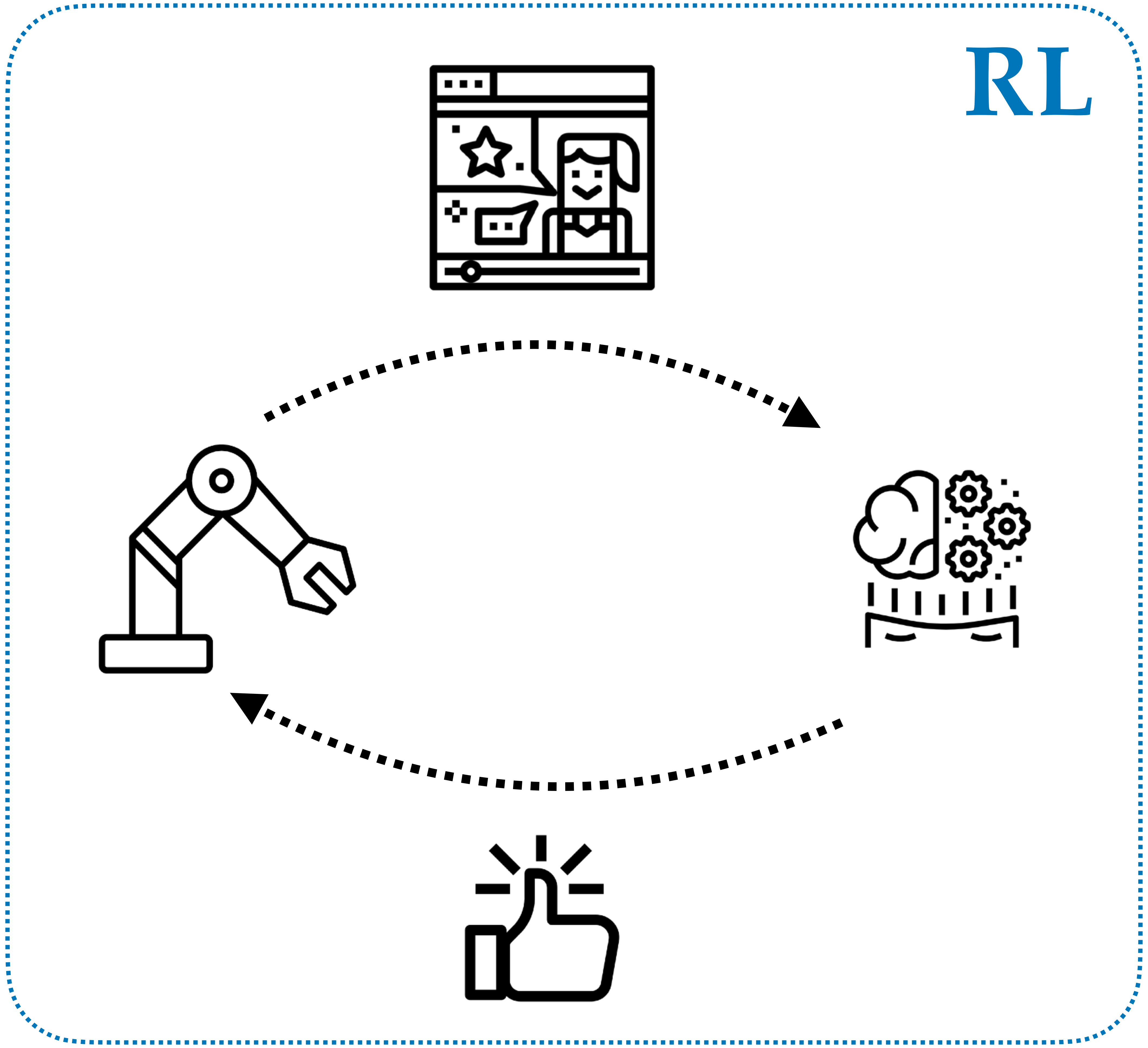


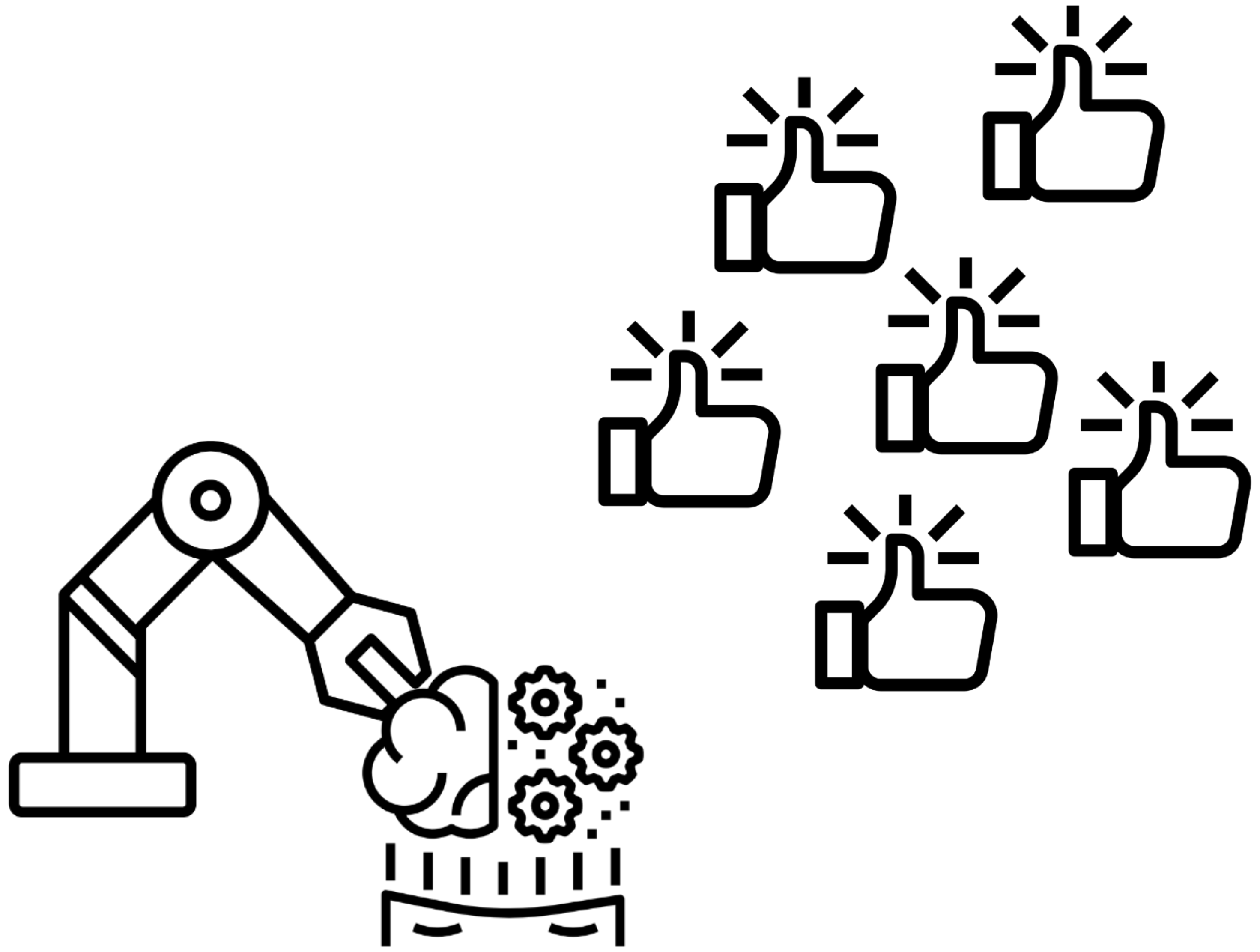
RS policy (i.e. the algorithm)



Other factors (UI, content-creators etc.)

Long-term-"value" systems

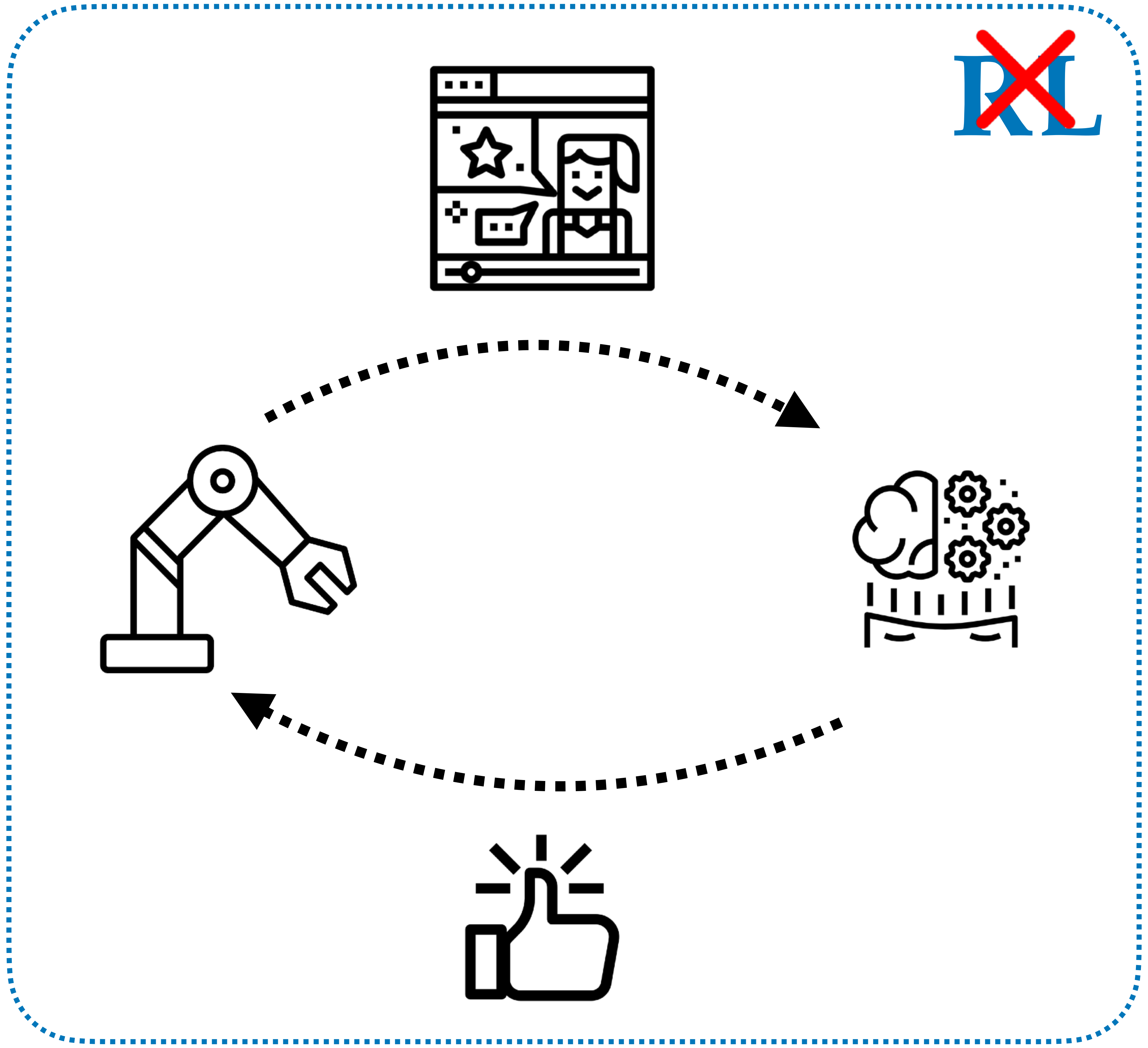




System will actively try to change the user by default!

[Krueger et. al, 2020] Hidden Incentives for Auto-Induced Distributional Shift

Long-term-“value” systems



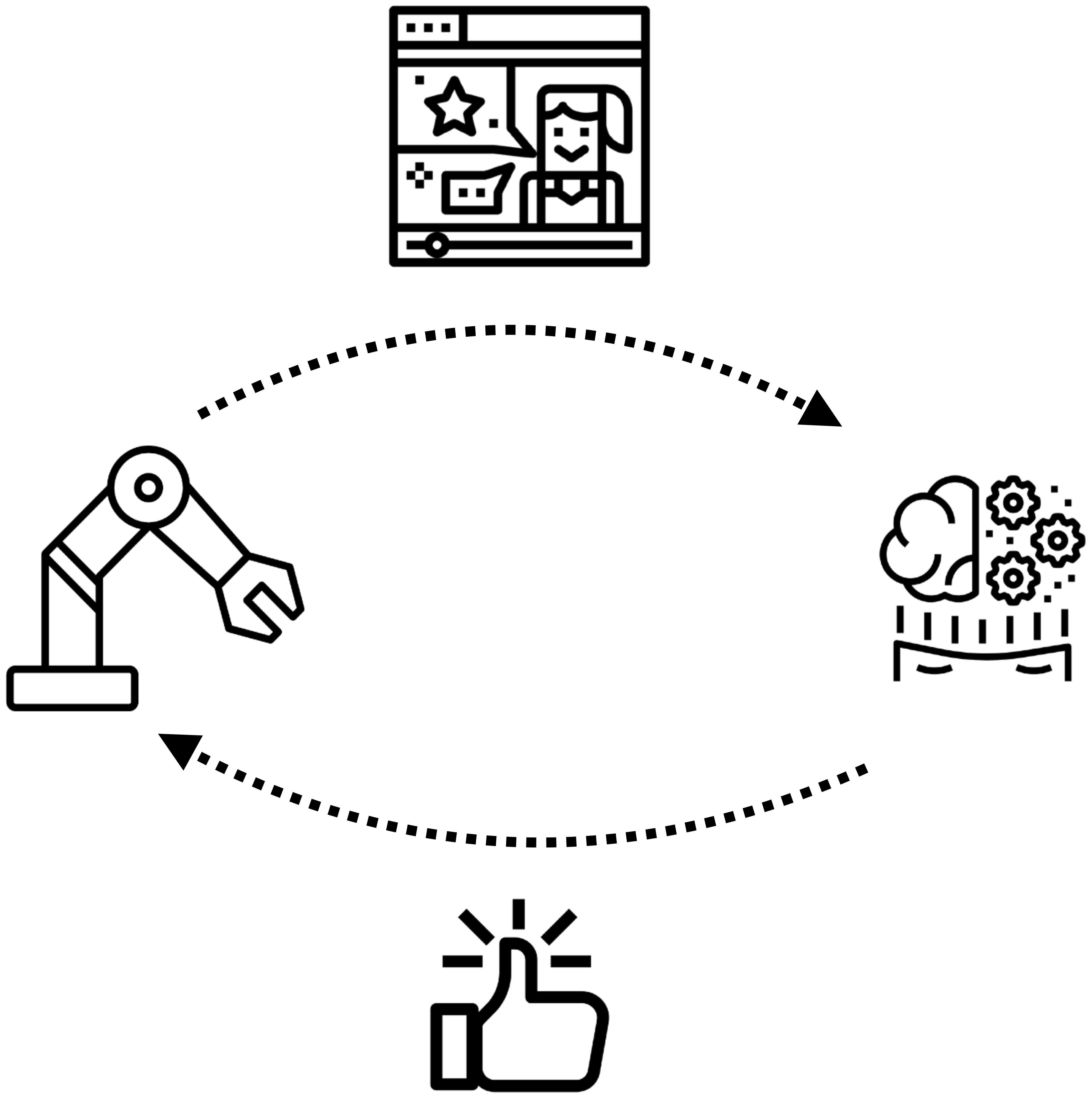
Preference shifts are assumed to be intrinsically value-less → *Misalignment!*

Make you easier to satisfy:

- Make you like common things
- Make you more predictable
  - Stabilize your preferences
  - Lead your choices to be less exploratory

[Krueger et. al, 2020] Hidden Incentives for Auto-Induced Distributional Shift

Myopic systems can still cause preference shifts



While myopia guarantees no active manipulation, it can still cause unwanted influence.

(Myopia is misaligned too)

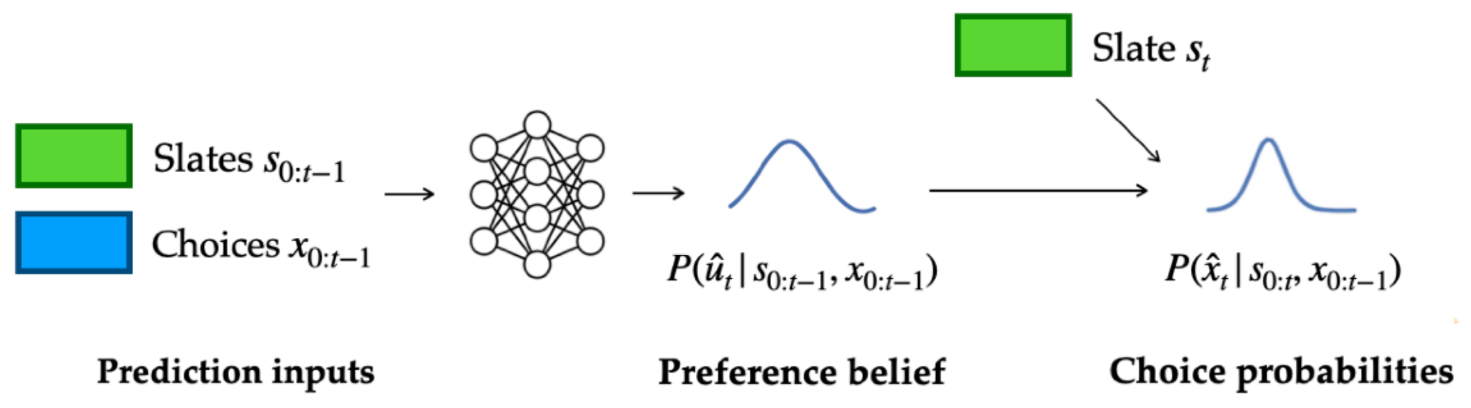
[Chaney et. al, 2017] How Algorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility

[Jiang et. al, 2019] Degenerate Feedback Loops in Recommender Systems

[Mansoury et. al, 2020] Feedback Loop and Bias Amplification in Recommender Systems

What I'll be talking about

1. Method for estimating preference shifts that would be induced by a policy



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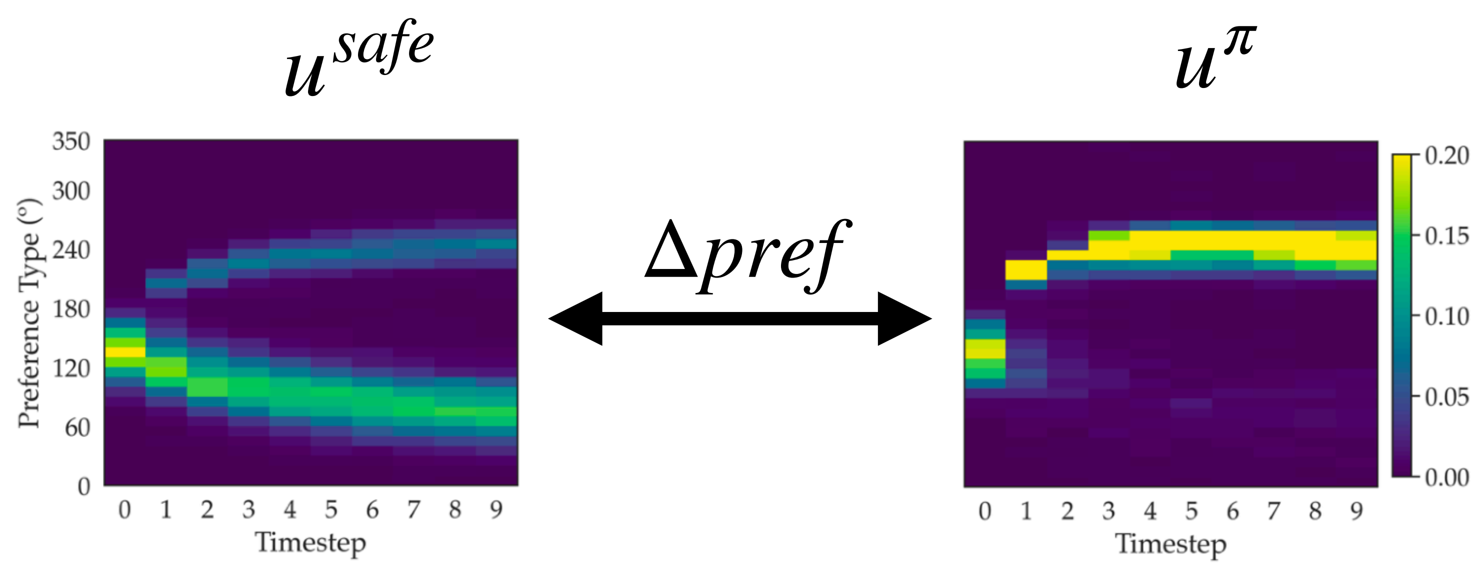
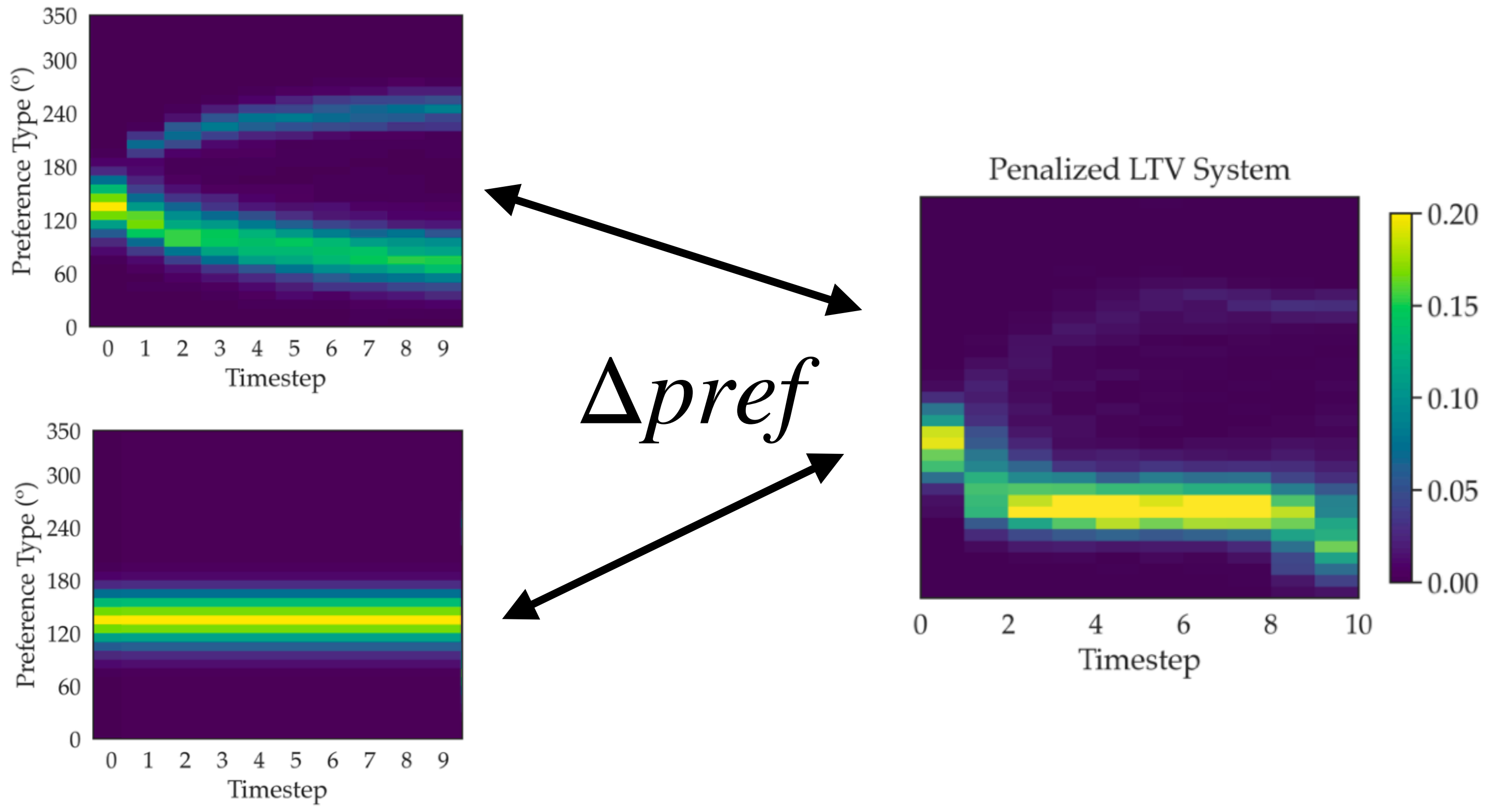
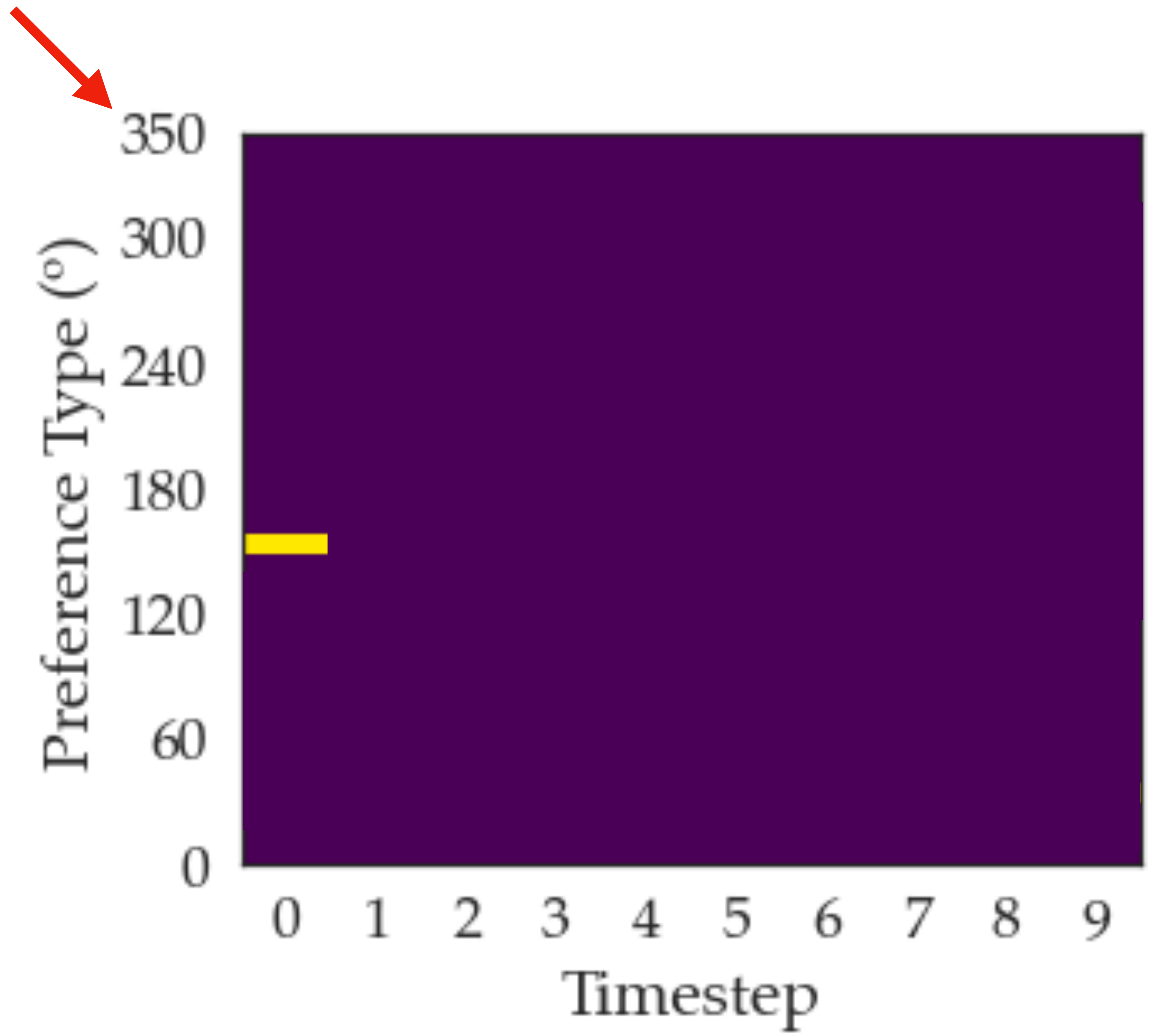
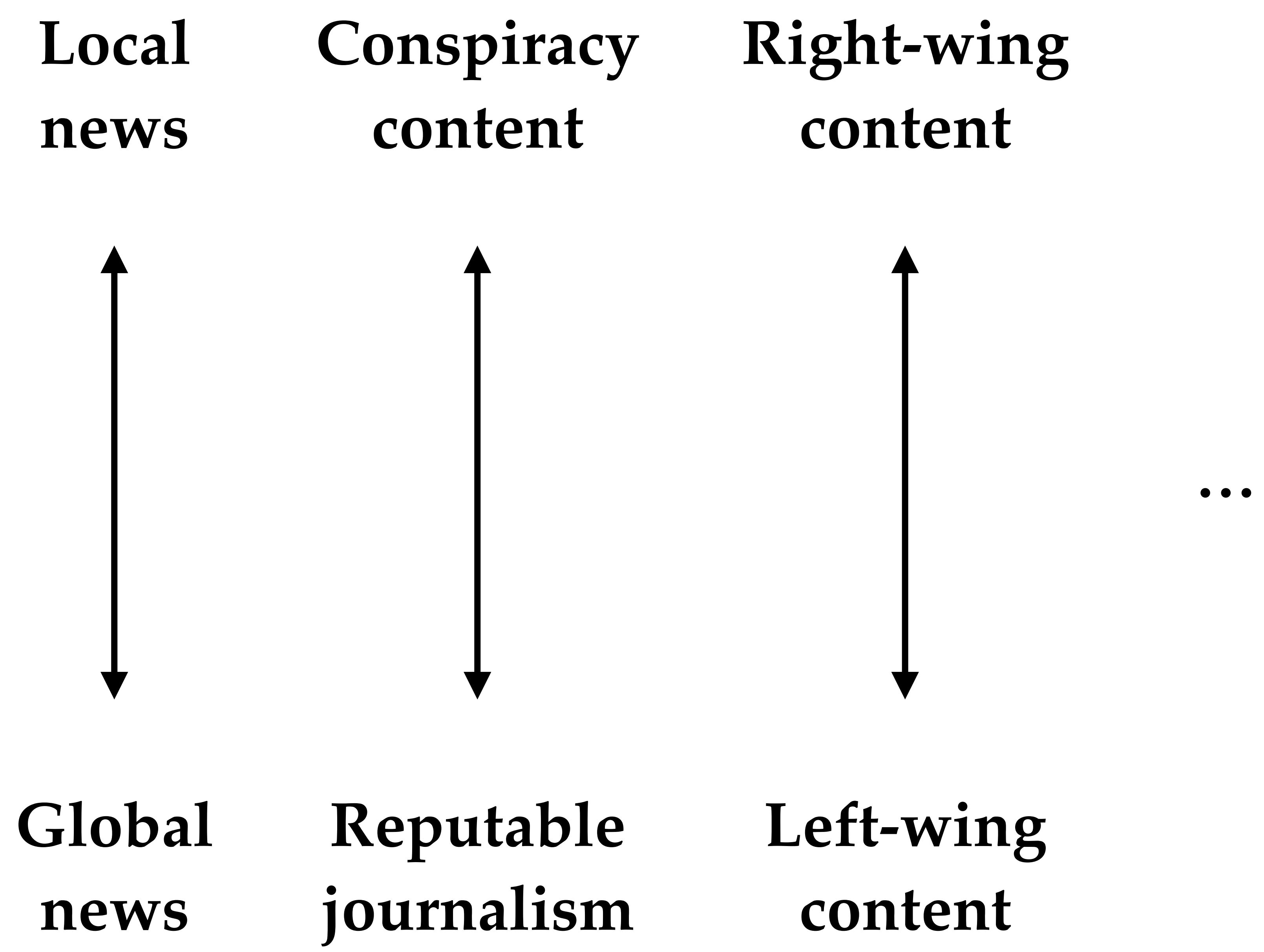


…which can be used to penalize RL training to actively avoid unwanted shifts



Preference influence? Preliminaries





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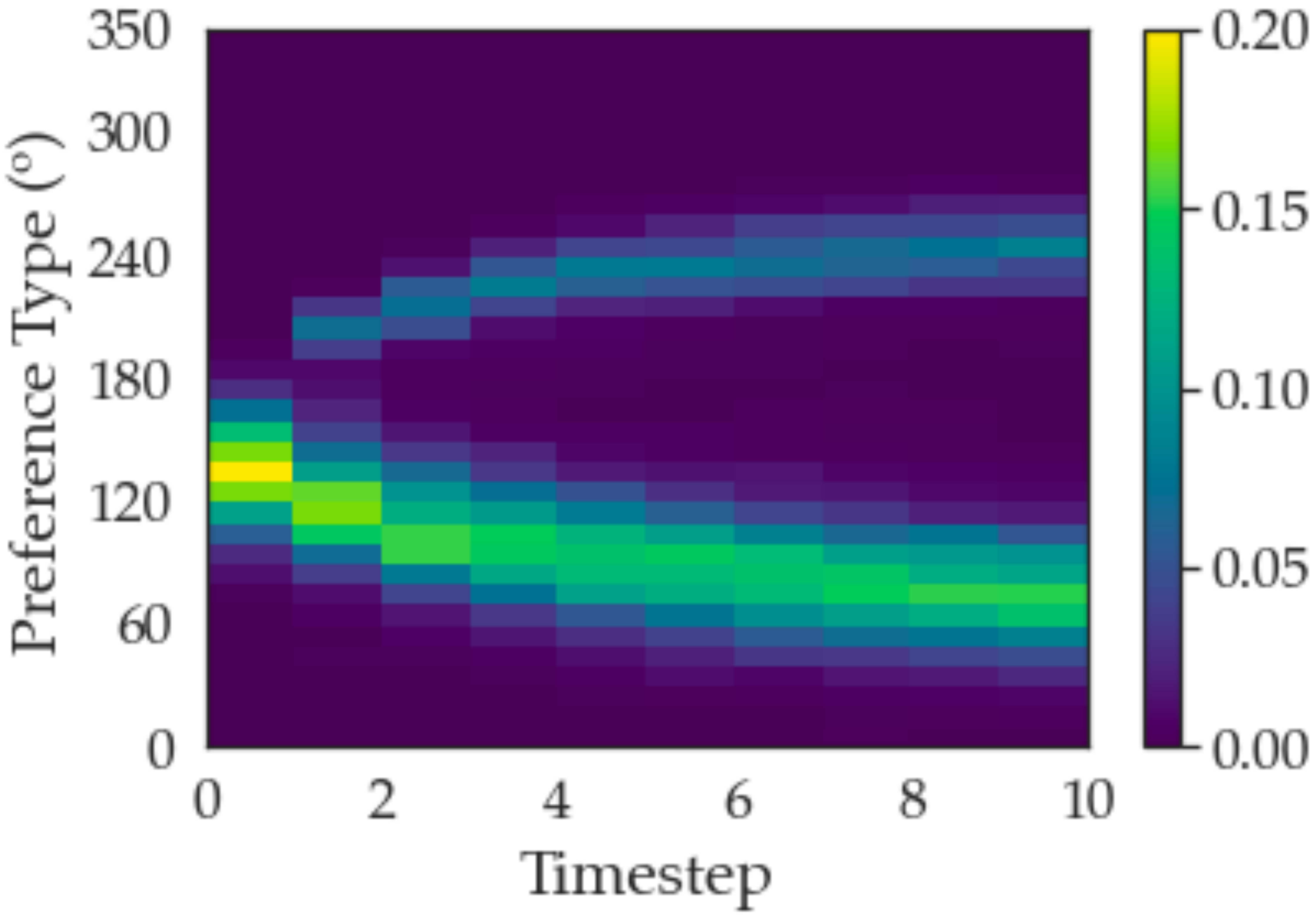


Sensationalized news

Reputable journalism

Policy-induced preference shifts

Learning model of human preference dynamics

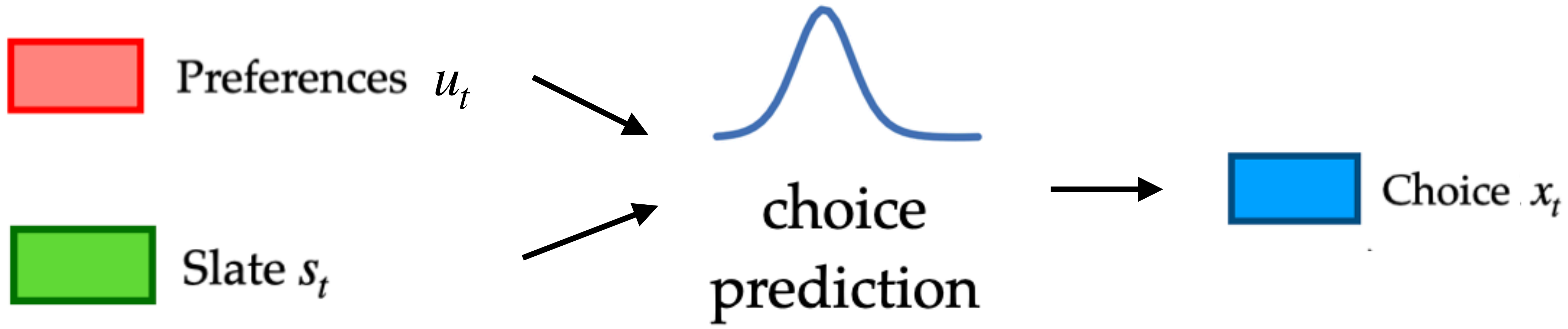
Preferences $u_t \in \mathbb{R}^d$

Slate s_t

Choice $x_t \in \mathbb{R}^d$

True Value r_t^* ?

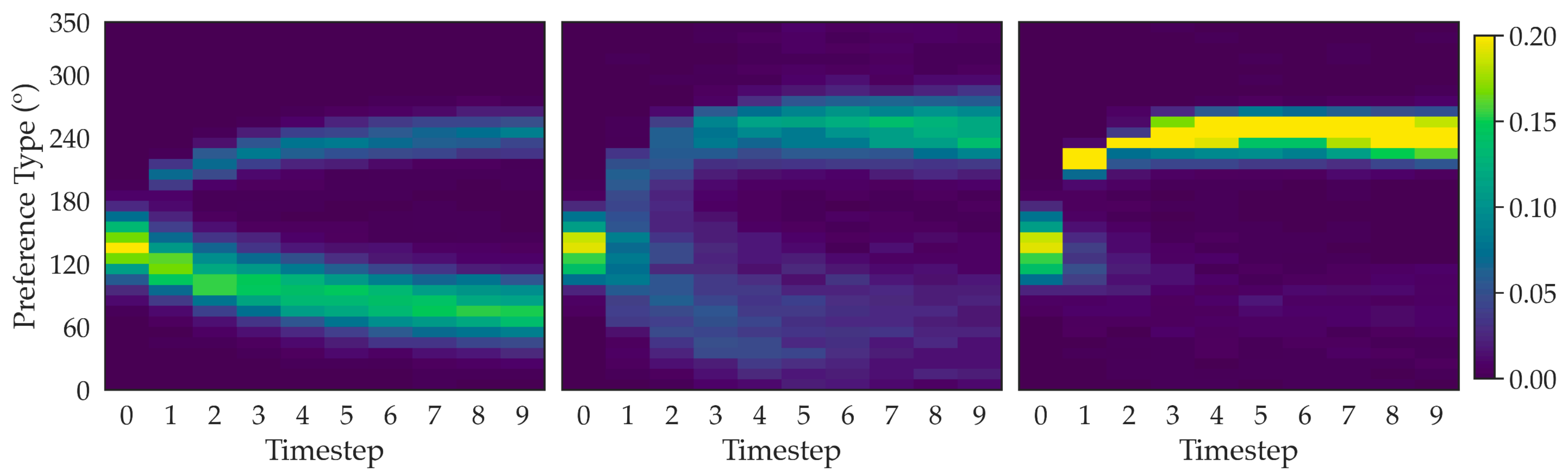
Assume human *choice model* is known

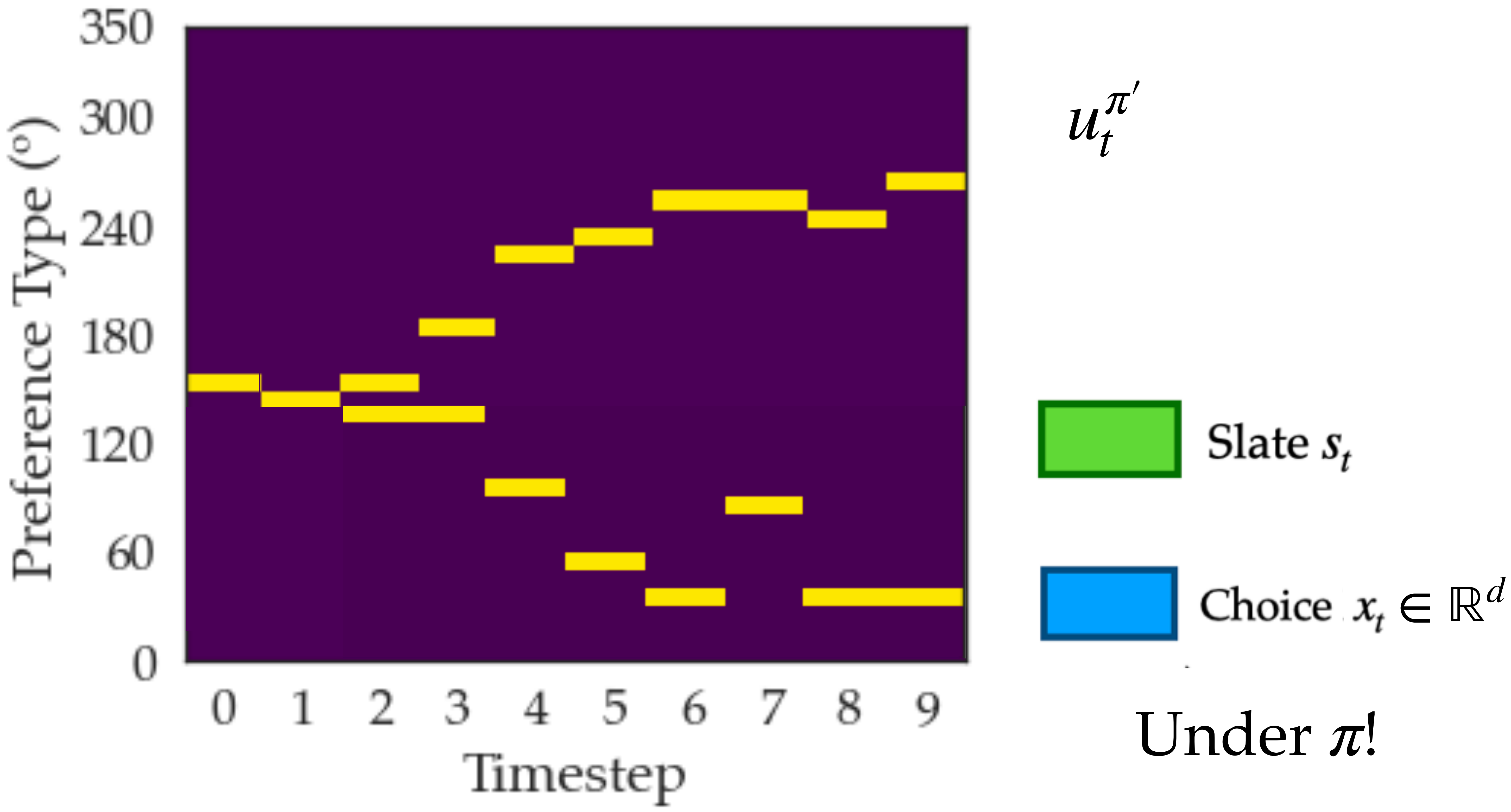


(Boltzmann rational)

Engagement Value $\hat{r}_t^{u_t} = u_t^T x_t$

Estimating counterfactual internal states





Under π!

Given $s^{\pi}_{0:T}, x^{\pi}_{0:T}$, estimate $u^{\pi'}_{0:T}$

Oracle access to internal state dynamics

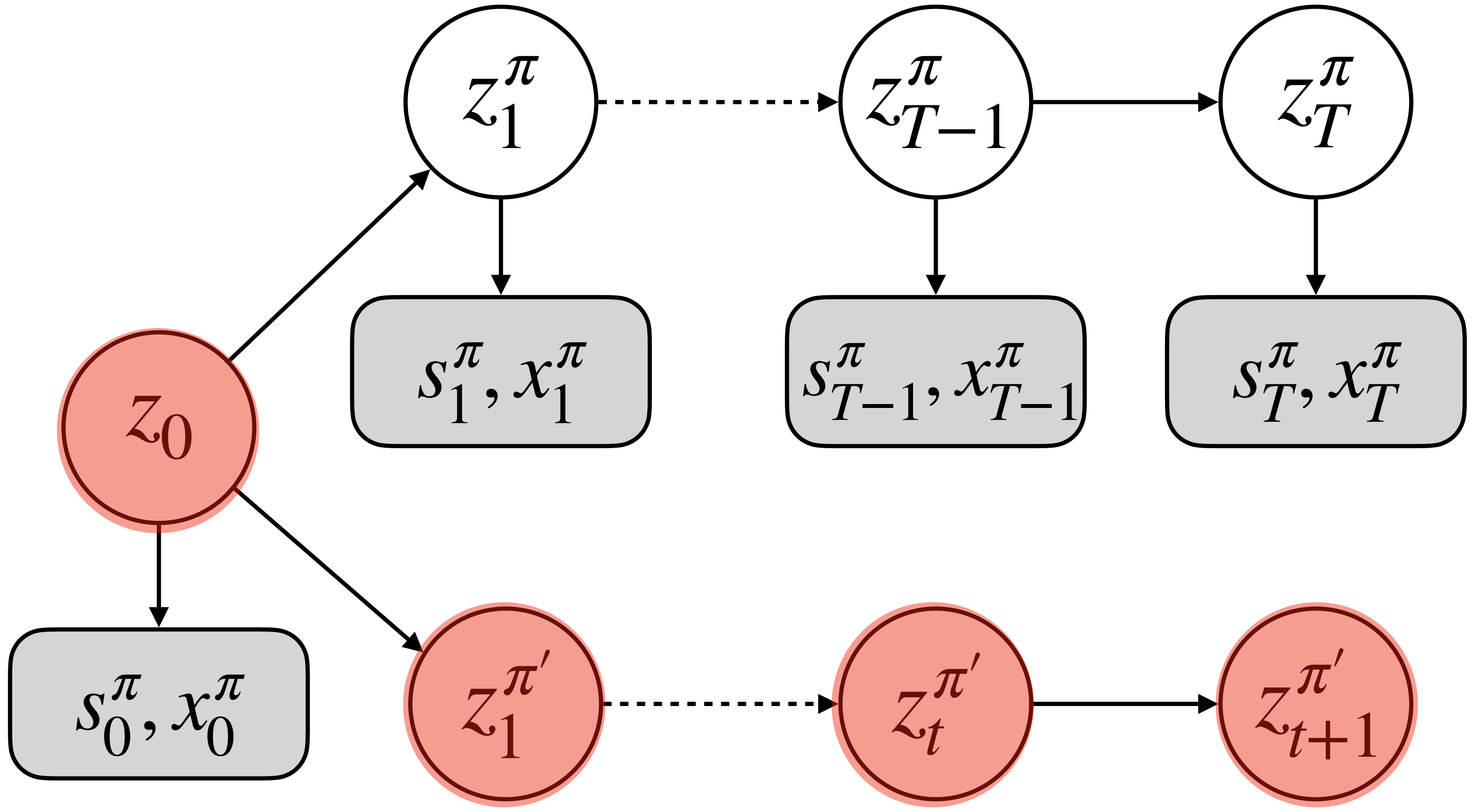
Preferences u_t

Beliefs

Psychological state

…

Internal state z_t

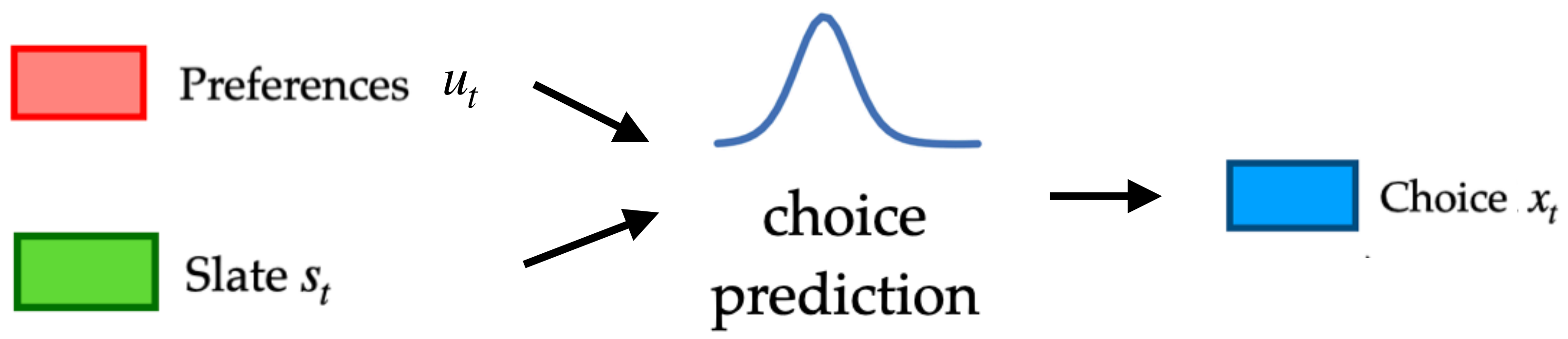


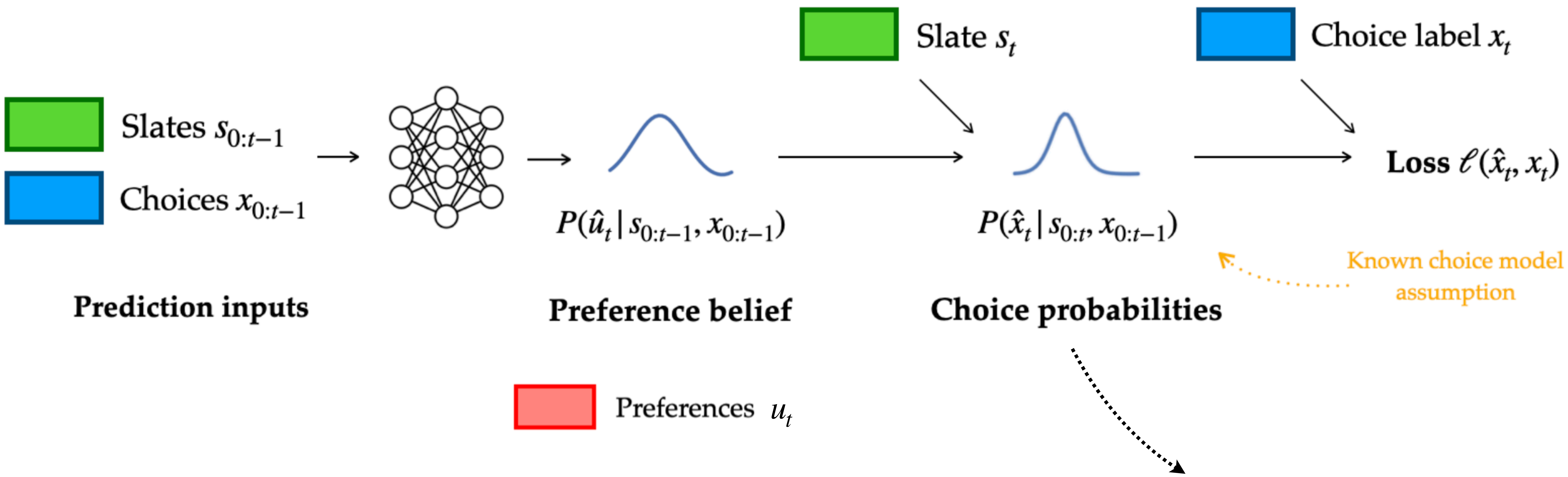
Given $s_{0:T}^{\pi}, x_{0:T}^{\pi}$, estimate $z_{0:T}$ $z_{0:T}^{\pi''}$

- Smoothing $P(z_0 \mid s_{0:T}^{\pi}, x_{0:T}^{\pi})$
- Forward prediction $P(z_t^{\pi'} \mid z_0)$

We don't have access to internal state dynamics!

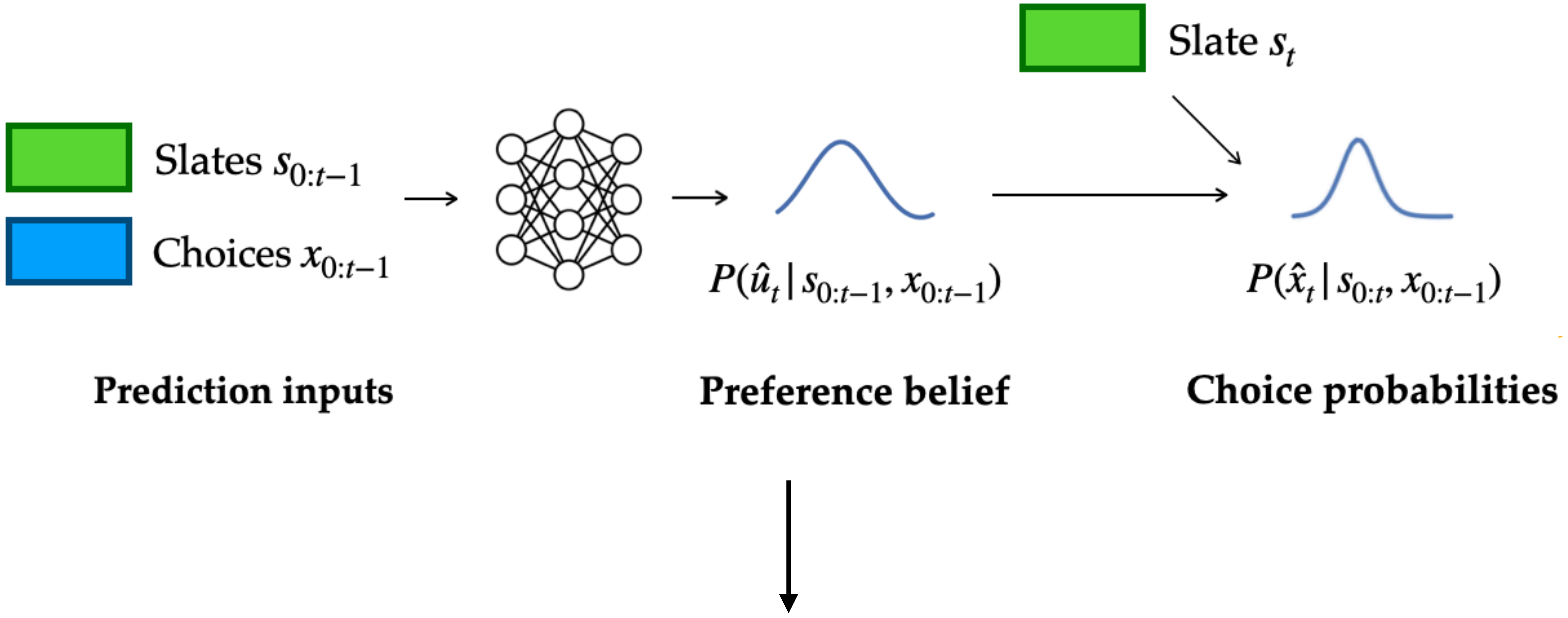
Approximating NHMM tasks without known dynamics





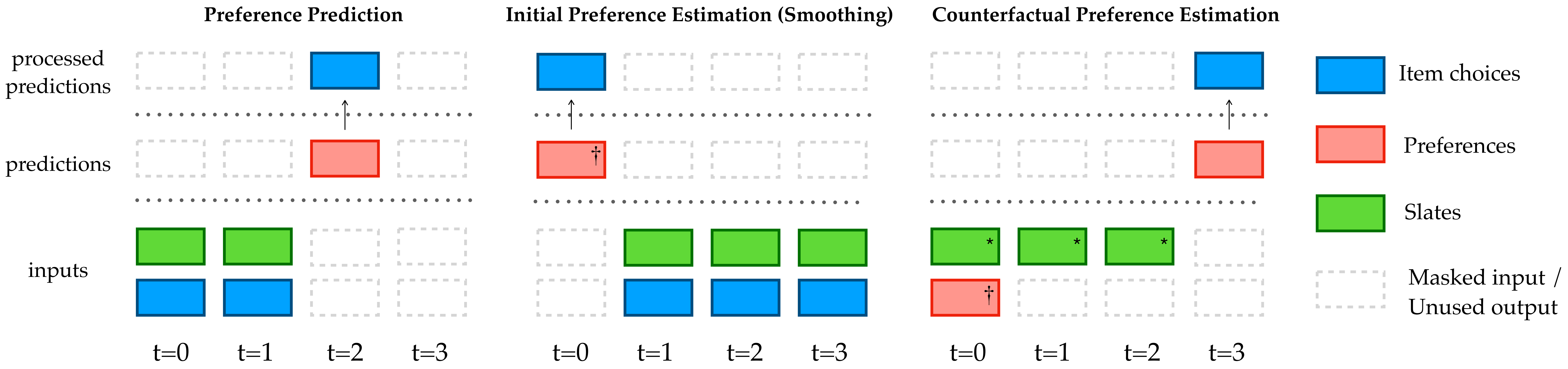
$$P(x_t|s_{0:t}, x_{0:t-1}) = \int_{u_t} P(x_t|u_t, s_t)P(u_t|s_{0:t-1}, x_{0:t-1})$$

Approximating NHMM tasks without known dynamics



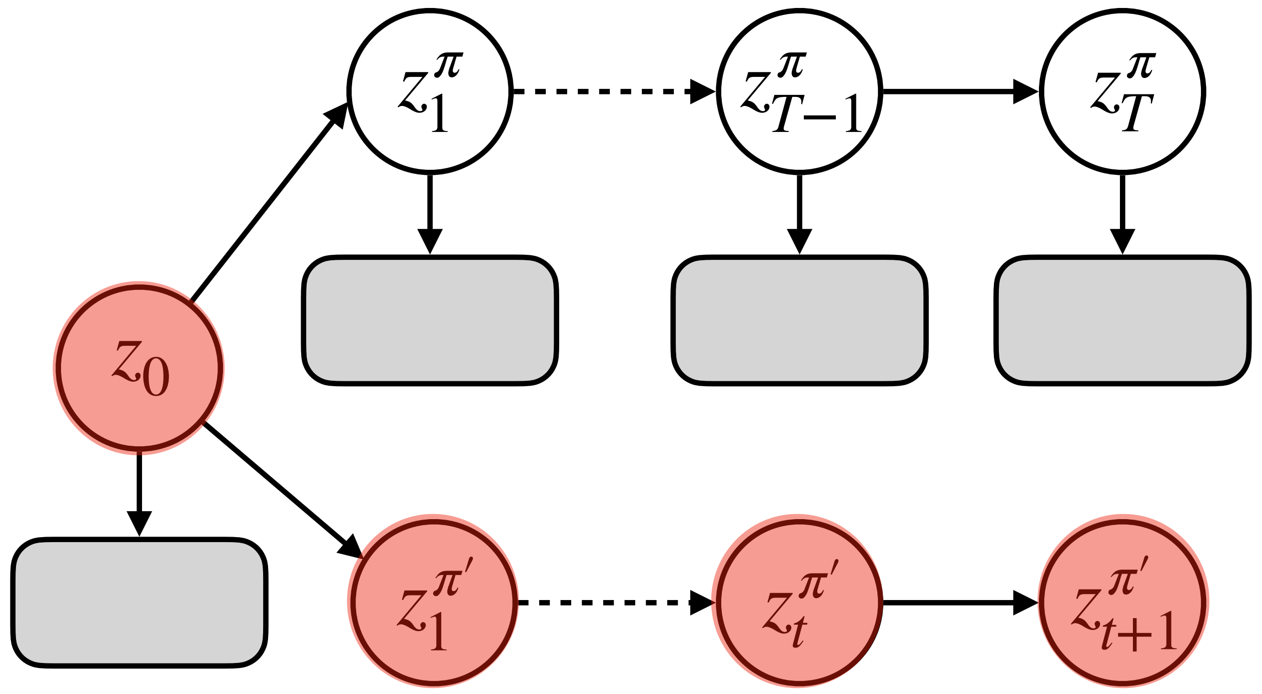
- **Future preferences** u_t
- **Initial preferences** u_0
- **Counterfactual preferences** (under different recsys policy π'): $u_t^{\pi'}$

Learning model of human preference dynamics



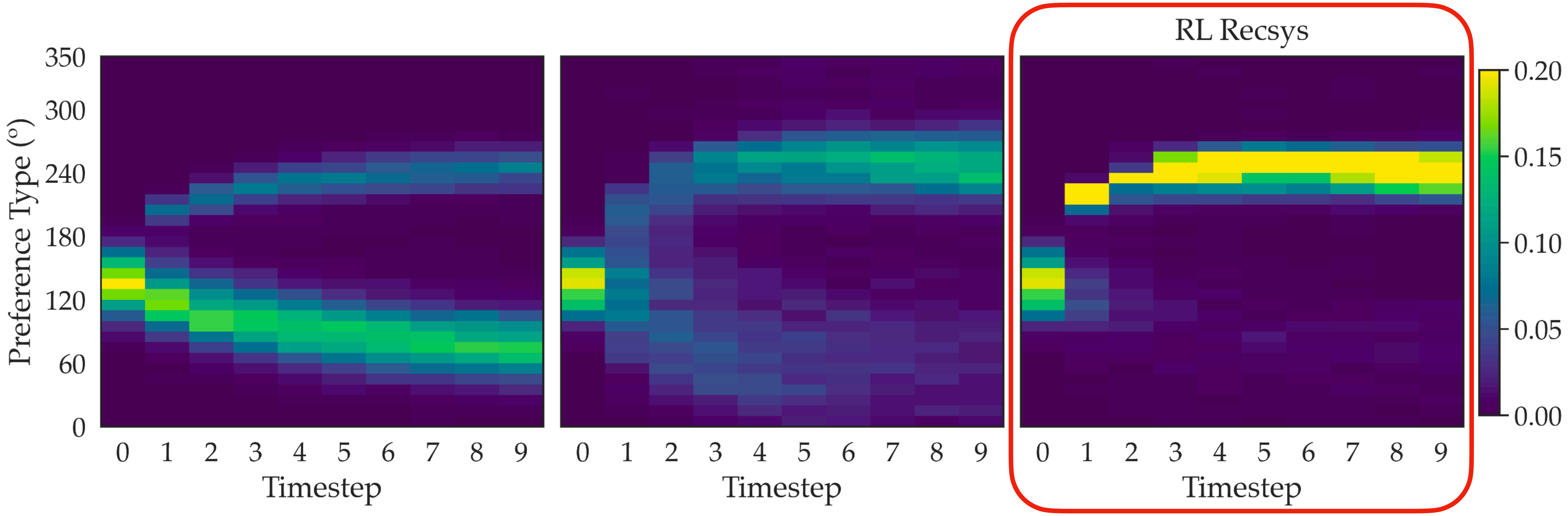
What we get $P(u_0|x_{1:t}, s_{1:t})$

What we want $P(u_0|x_{0:t}, s_{0:t}) \propto P(x_0, s_0|u_0)P(u_0|x_{1:t}, s_{1:t})$



Policy-induced preference shifts

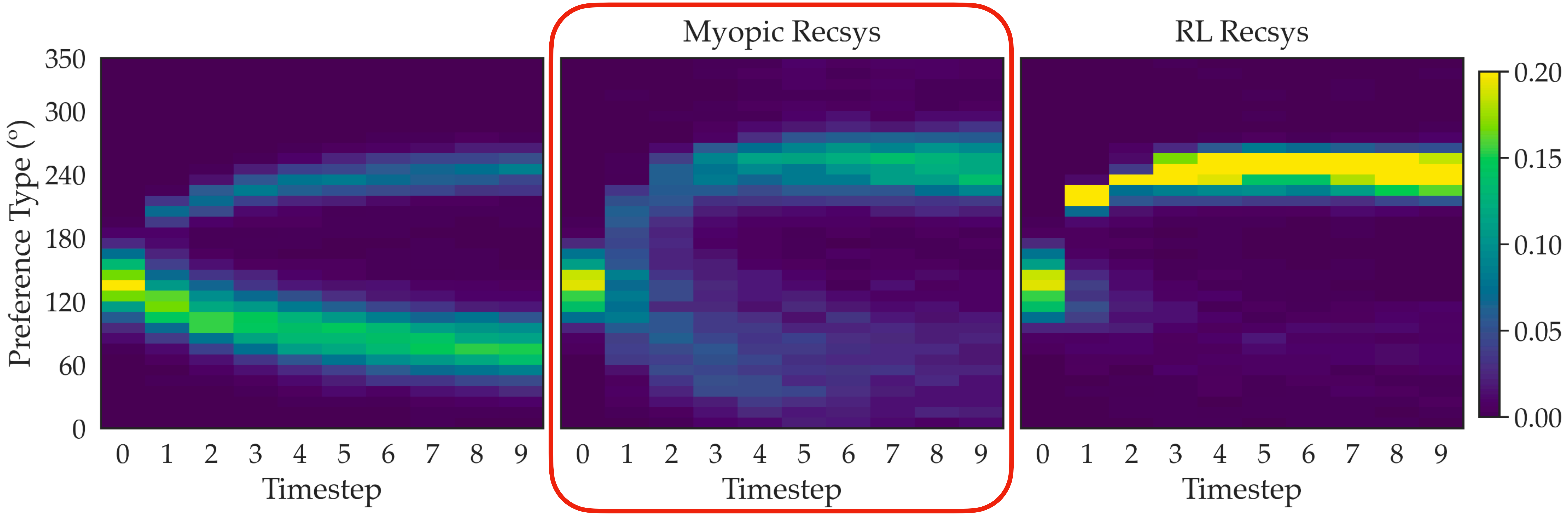
RL RS-induced preference shifts



High engagement

Likely
undesirable shifts?

Myopic RS-induced preference shifts



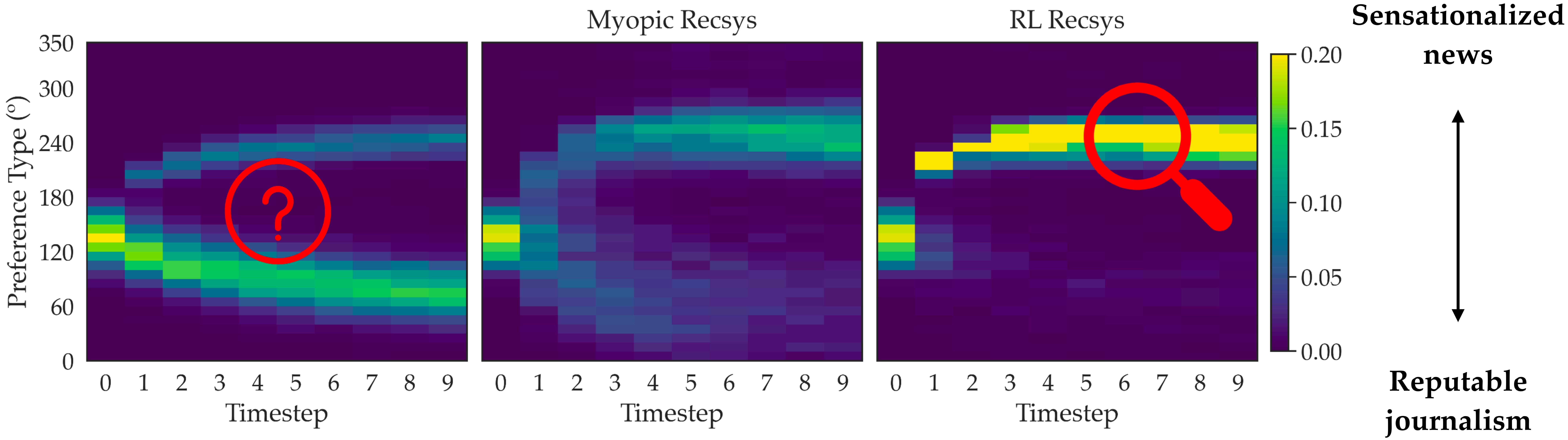
Medium engagement

Potentially undesirable shifts?

High engagement

Likely undesirable shifts?

What preference shifts do we want?



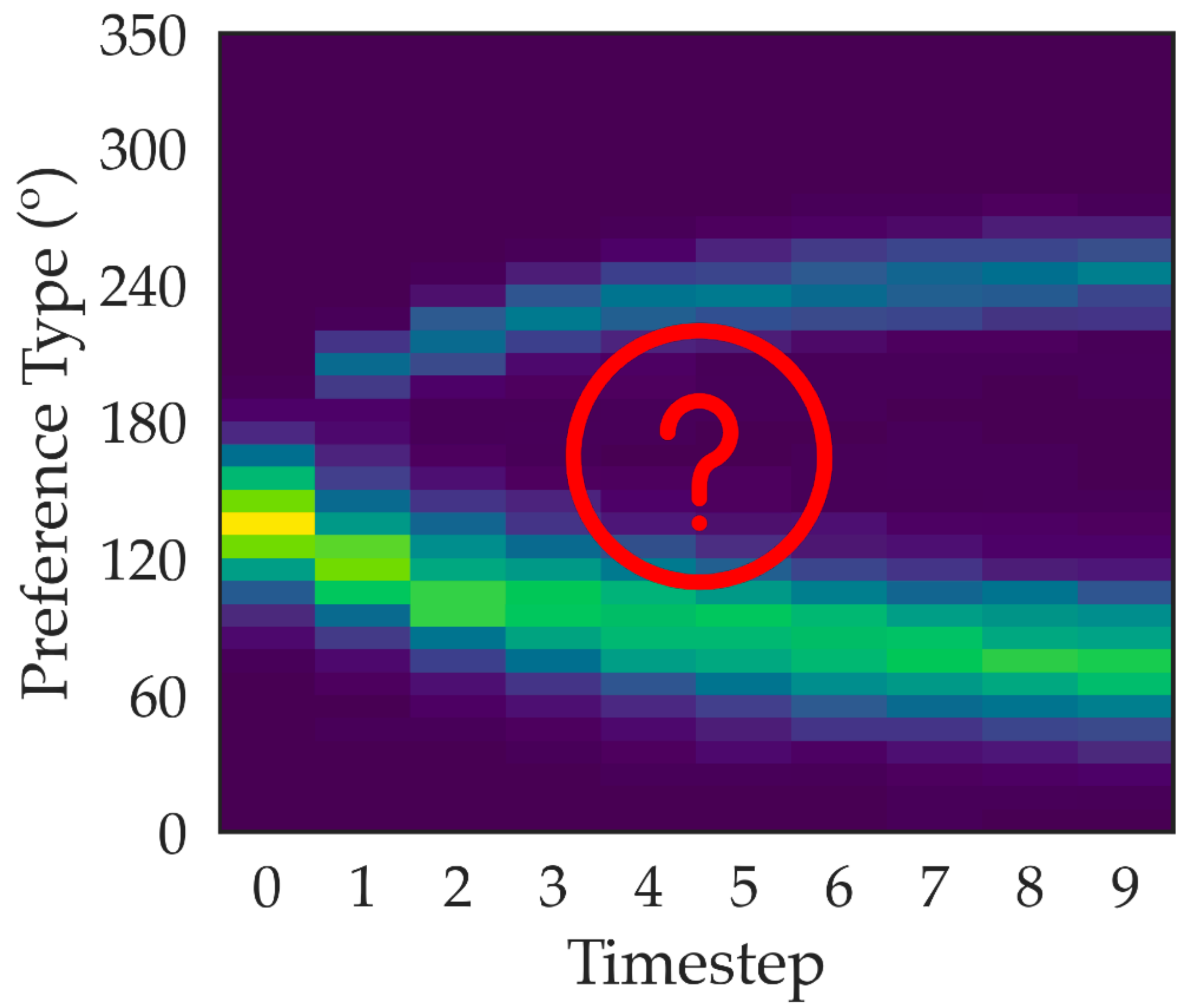
Medium engagement **High engagement**

"Desirable" shifts?

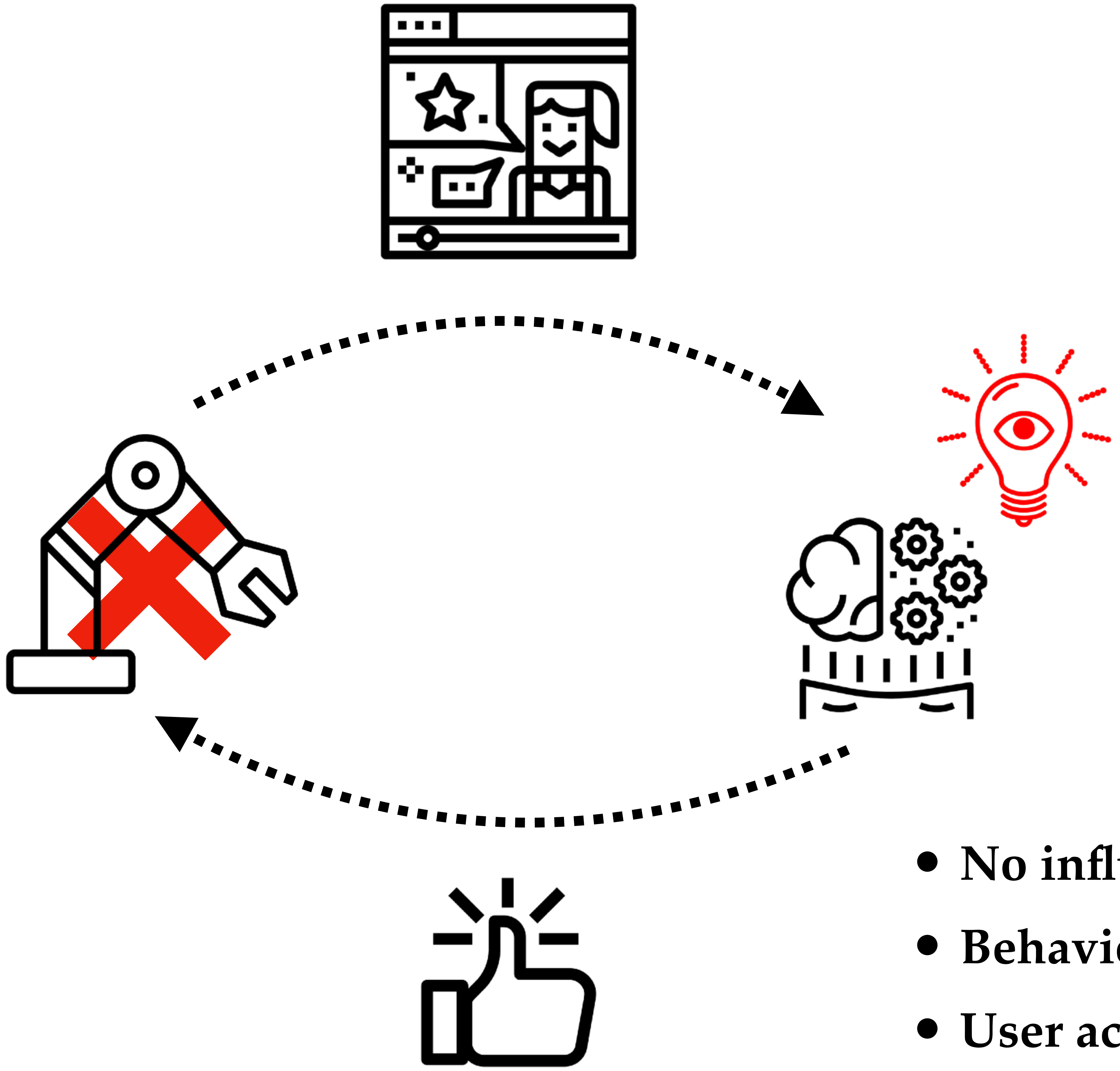
Potentially undesirable shifts?

Likely undesirable shifts?

Ideally, what would we want?

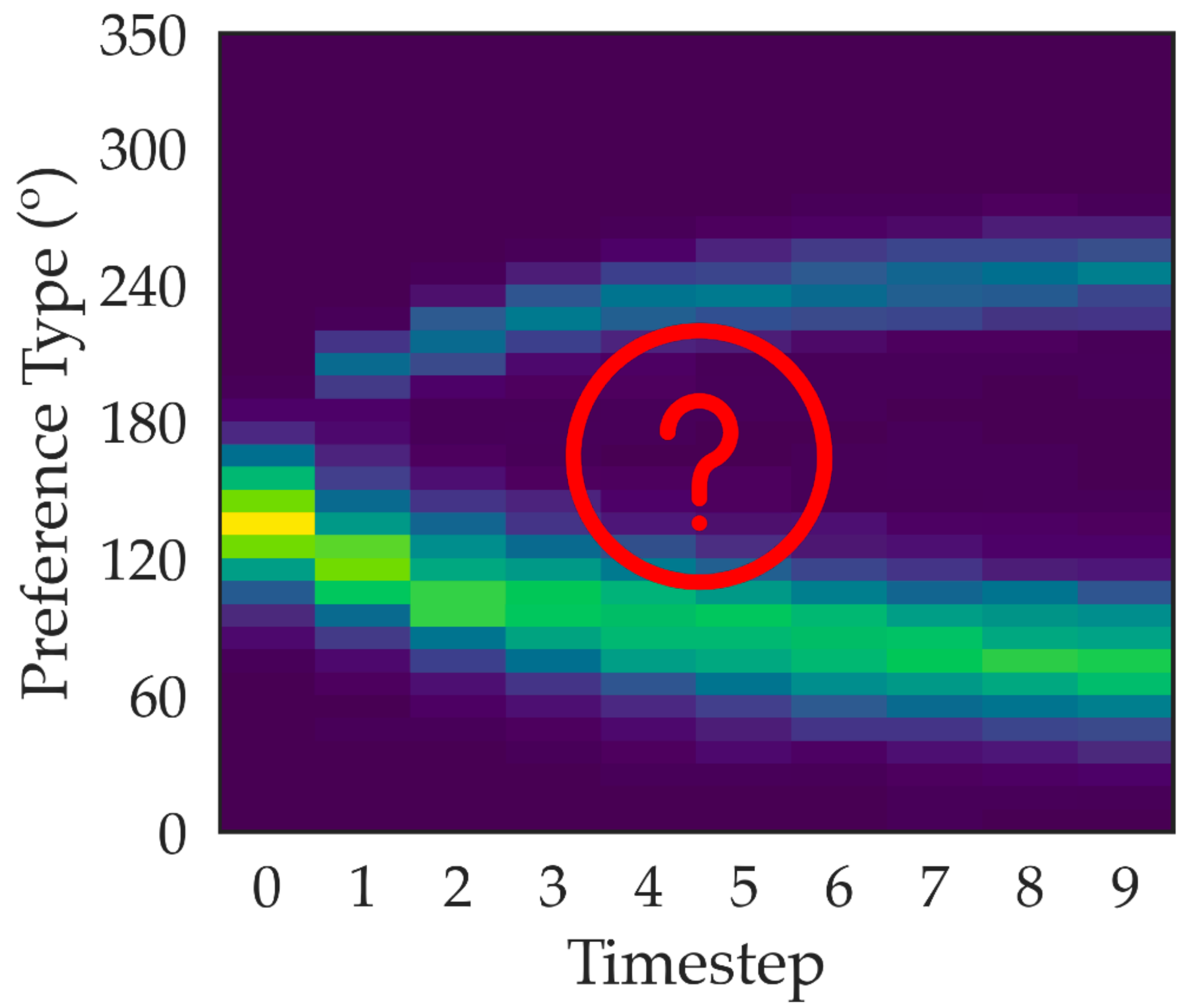


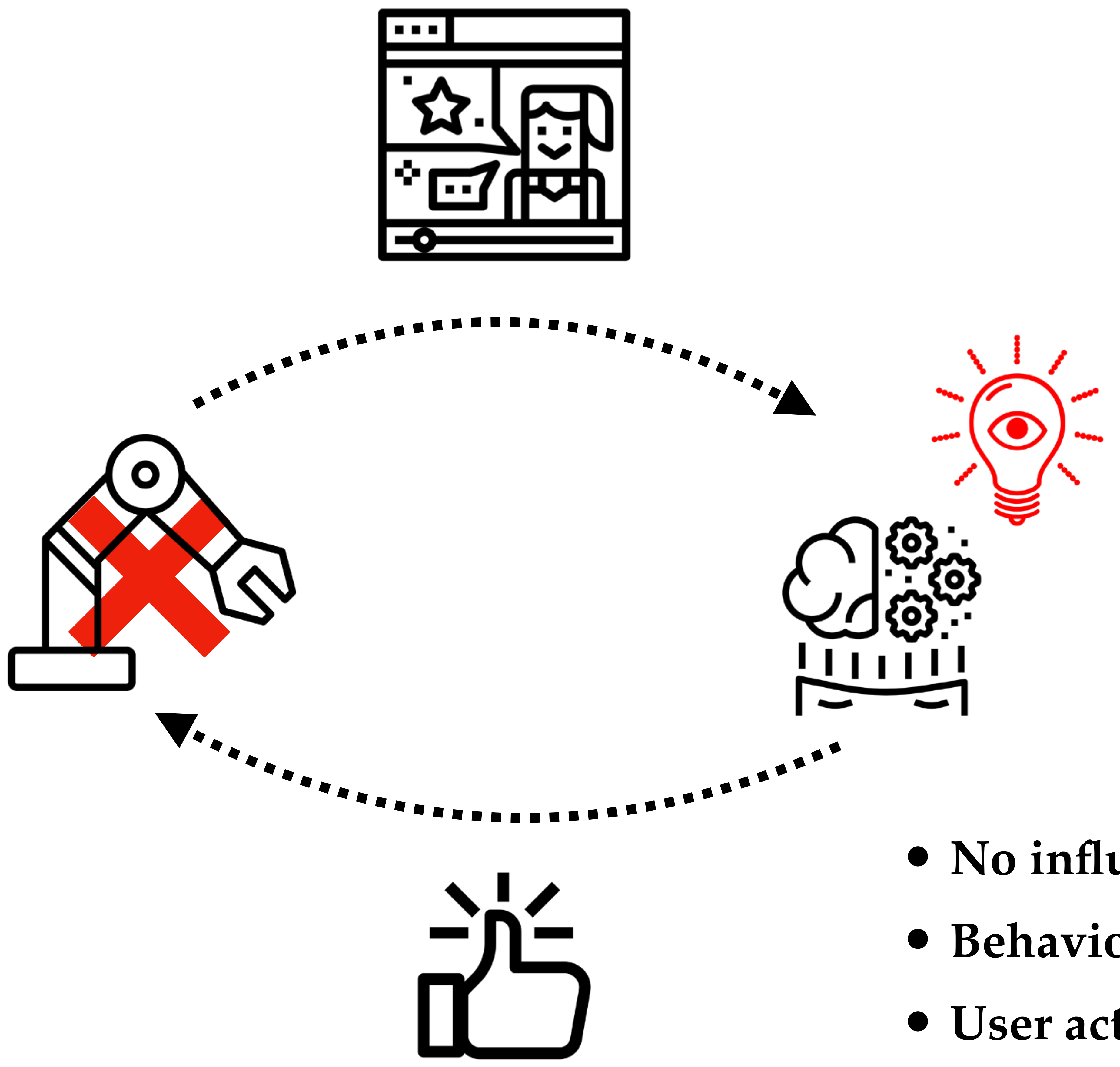
"Desirable" shifts?



- **No influence from RS**
- **Behavior under full information**
- **User acting in the interest of their "best-self"**

Ideally, what would we want?





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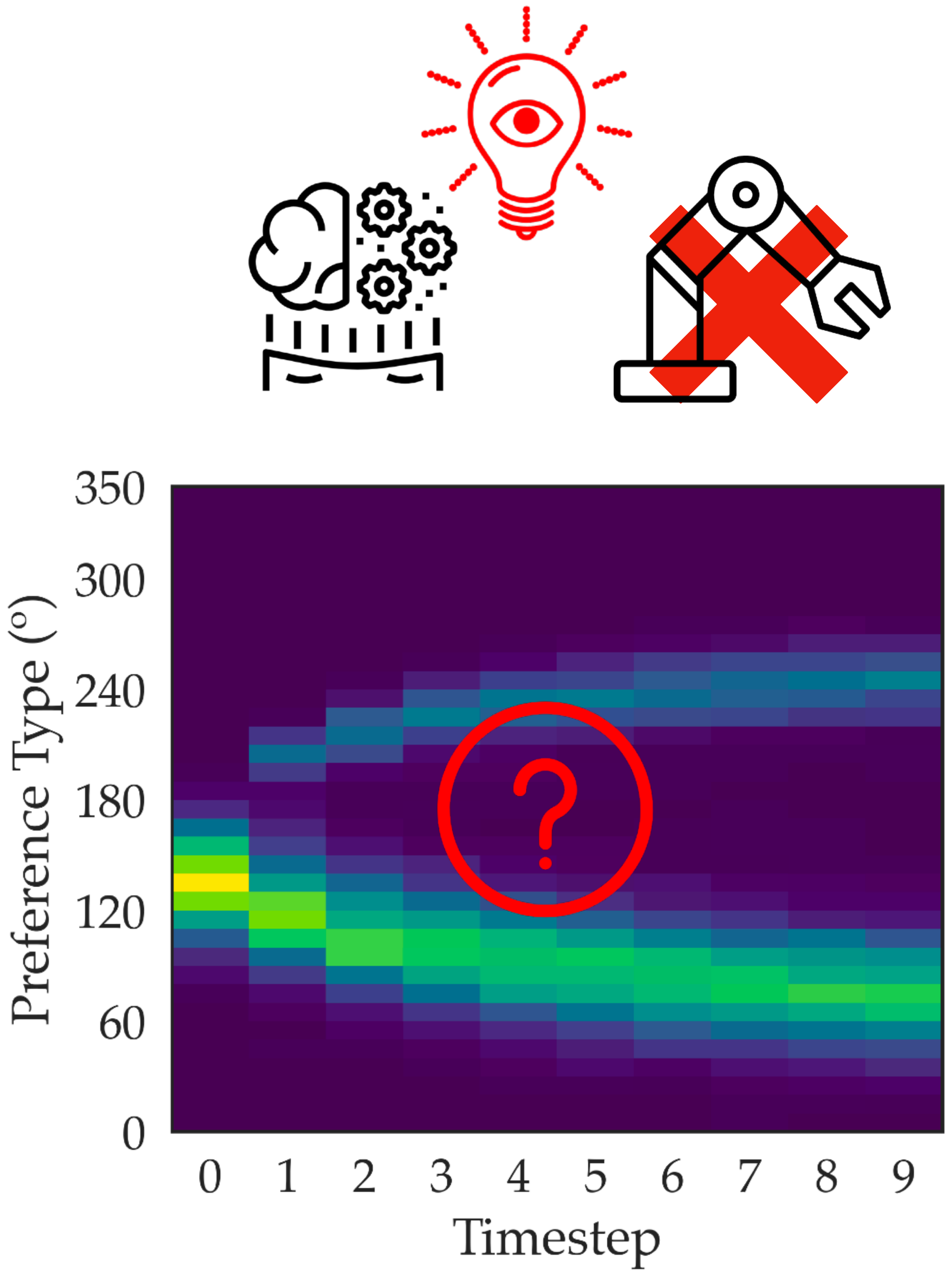
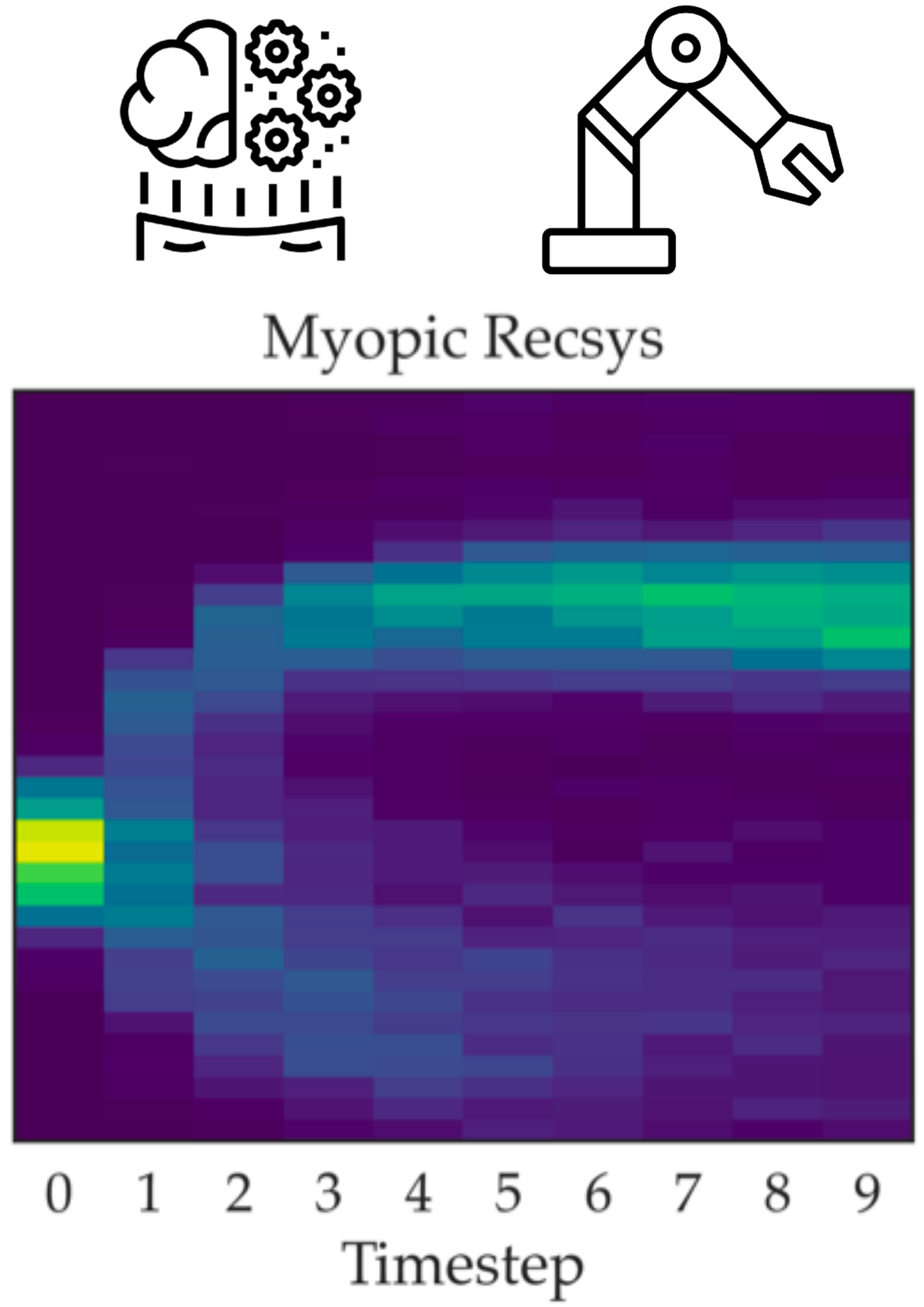
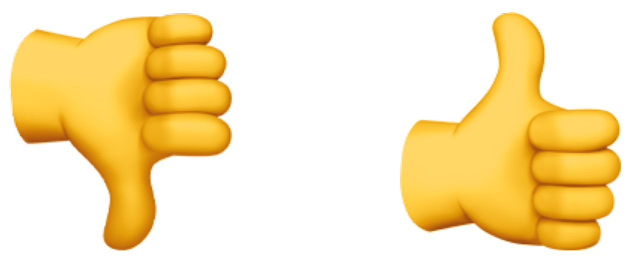


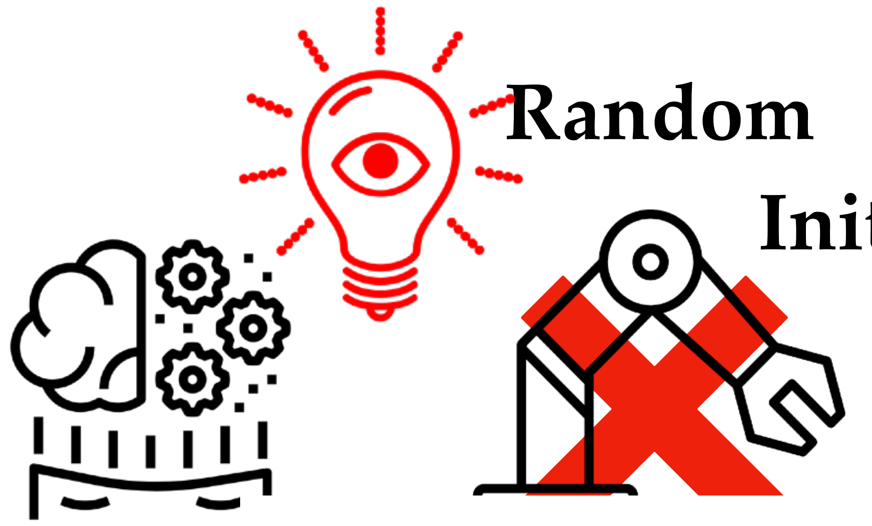
$\Delta pref$



Desirable shifts



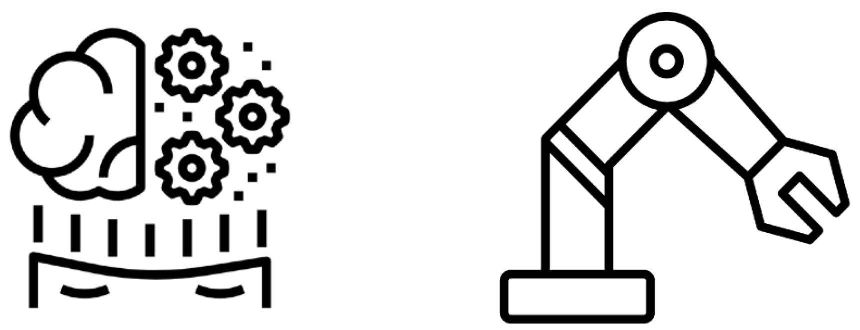
Realistically, what can we do?

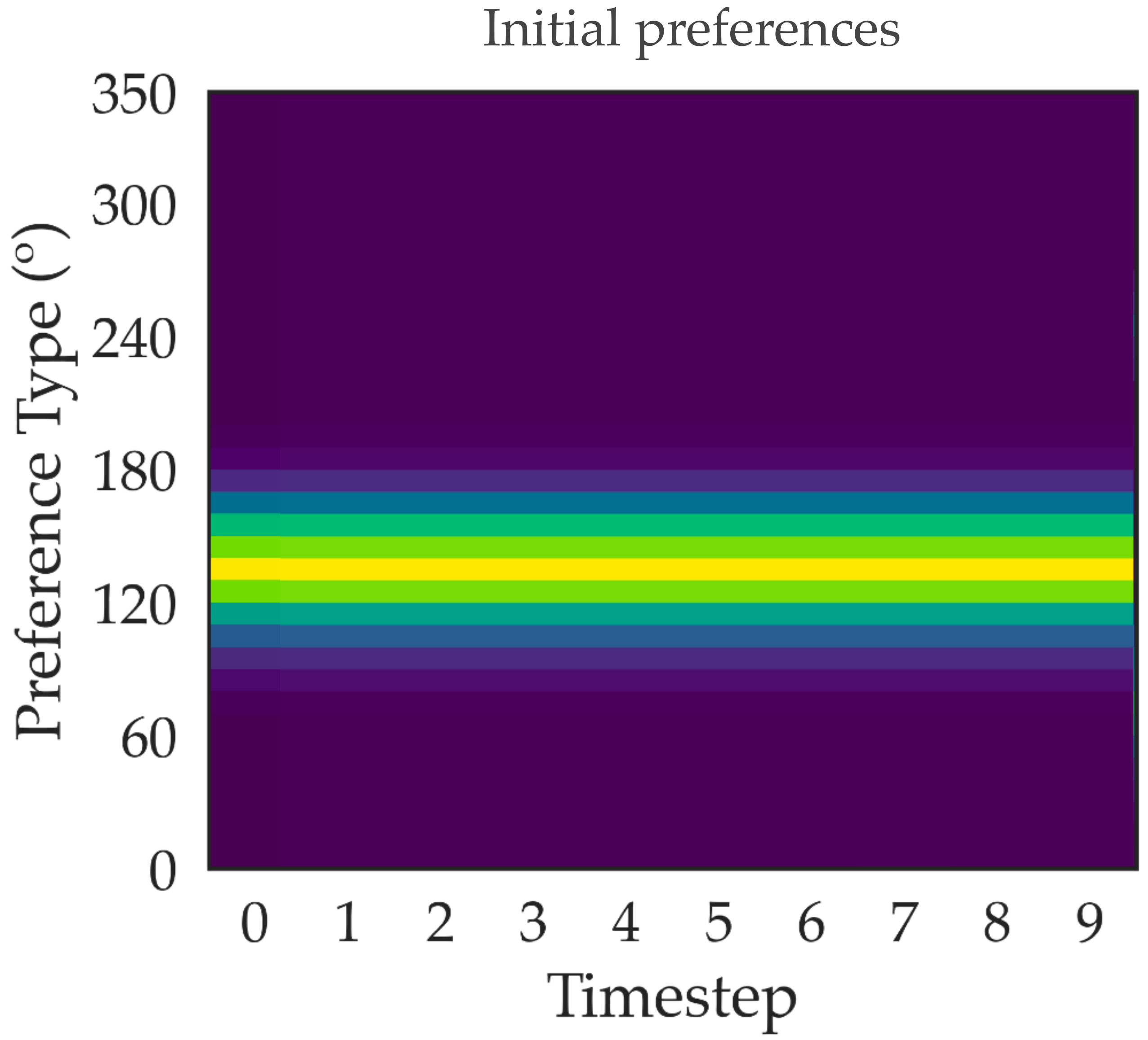


Random

Initial pref. - don't change anything!

Collective / political decision?





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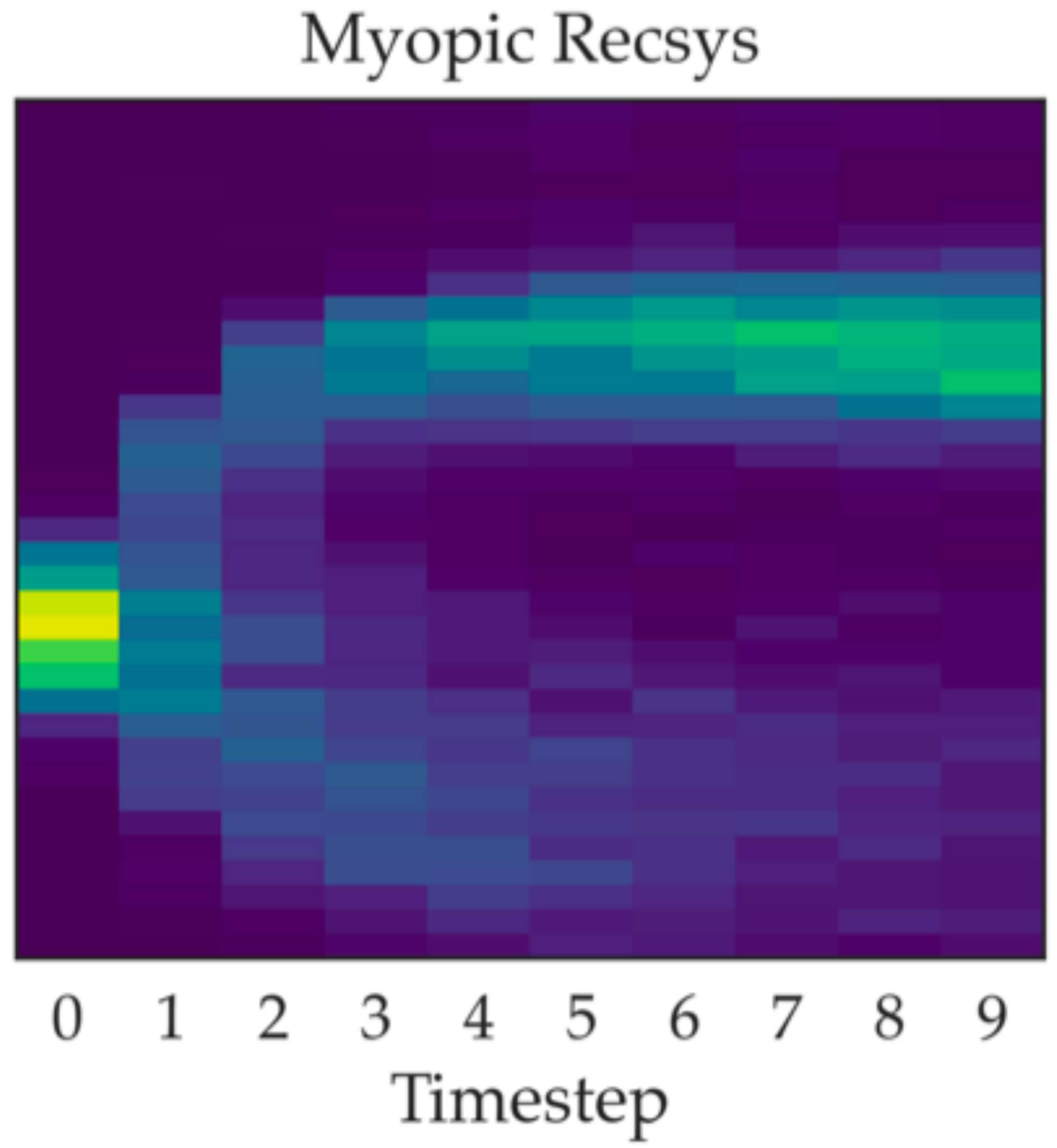
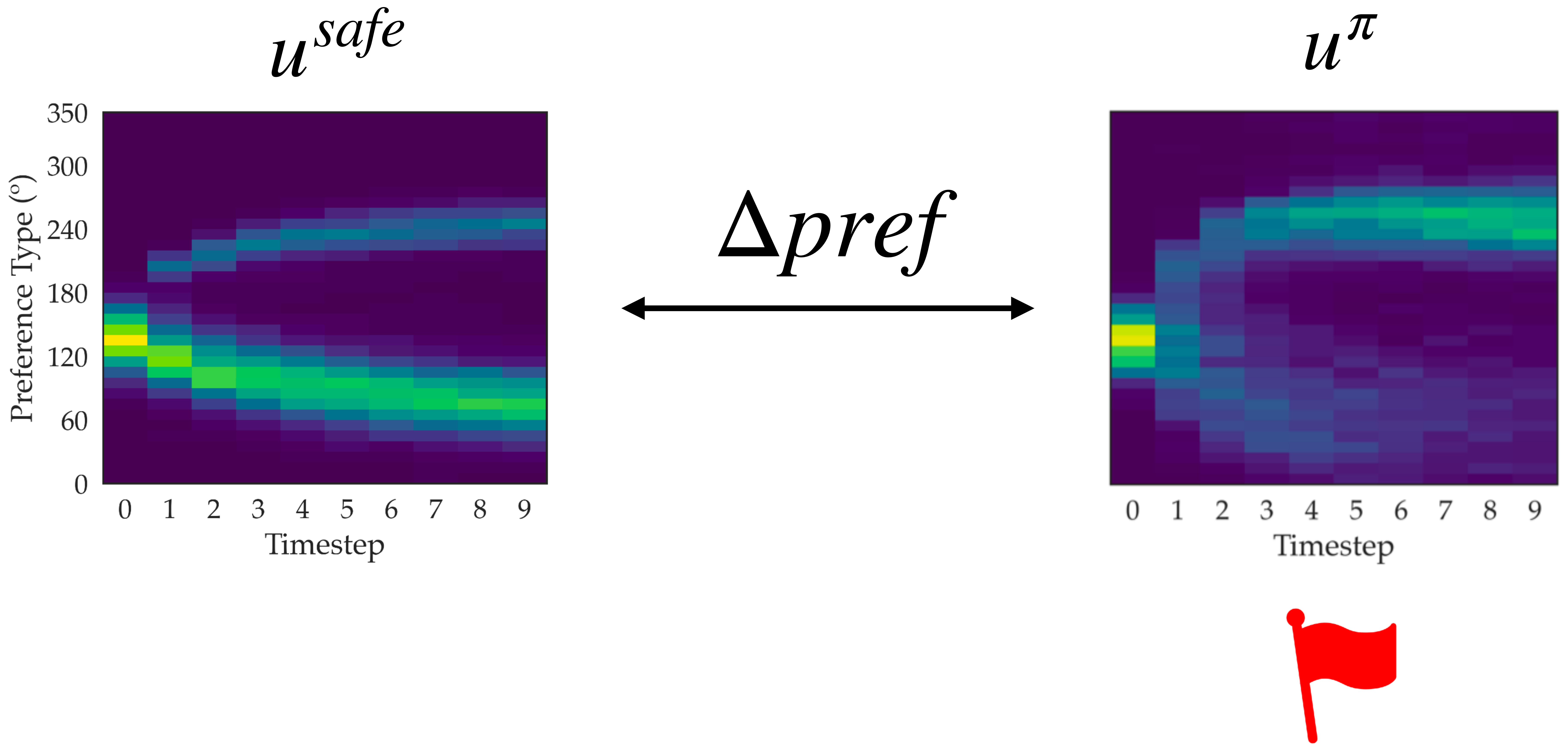


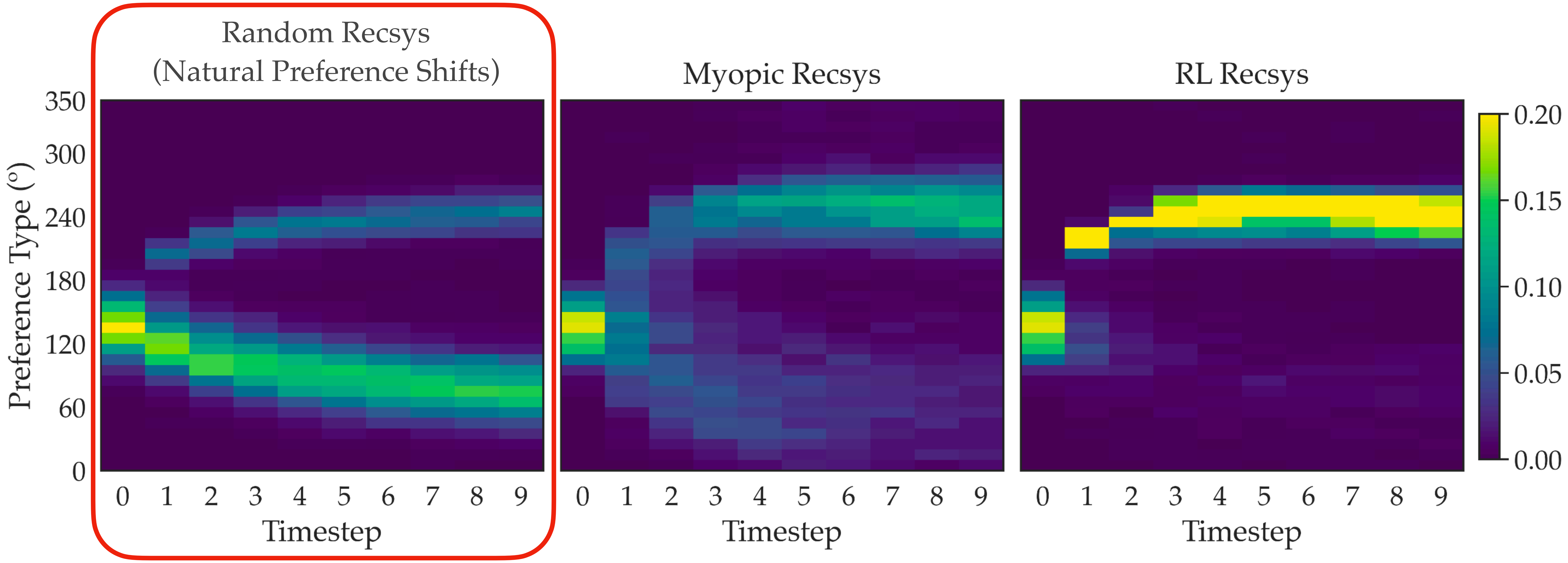
"Natural preference shifts" (NPS)

Realistically, what can we do?



A framework for creating <u>conservative metrics</u> for a policy π's degree of unwanted preference shift

What preference shifts do we want?



Low engagement	Medium engagement	High engagement
Safe shifts	Potentially undesirable shifts?	Likely undesirable shifts?

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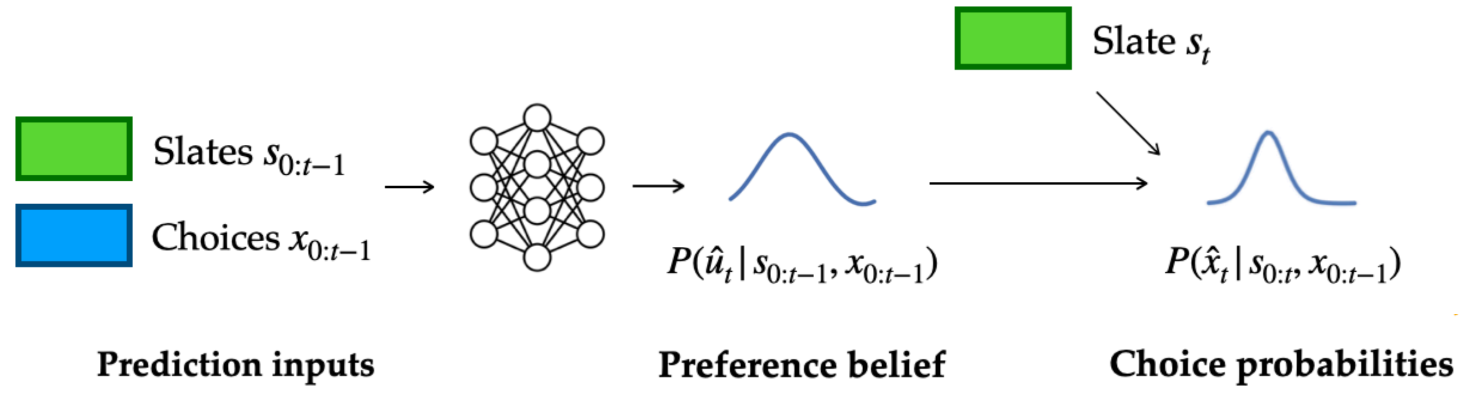

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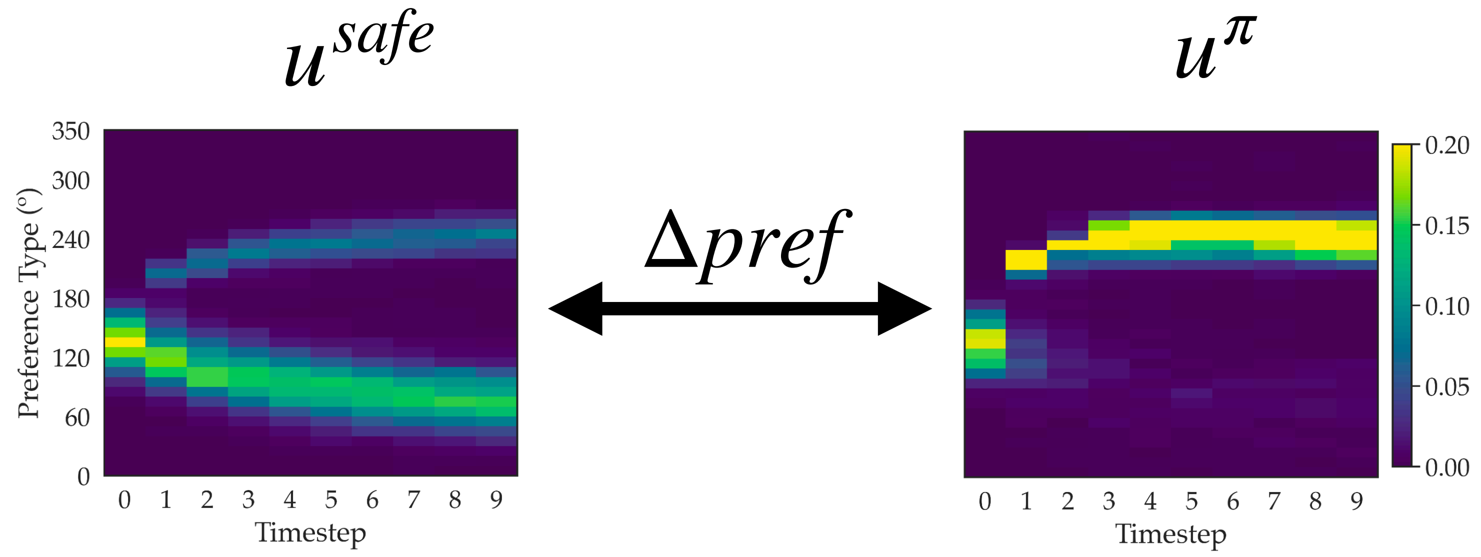
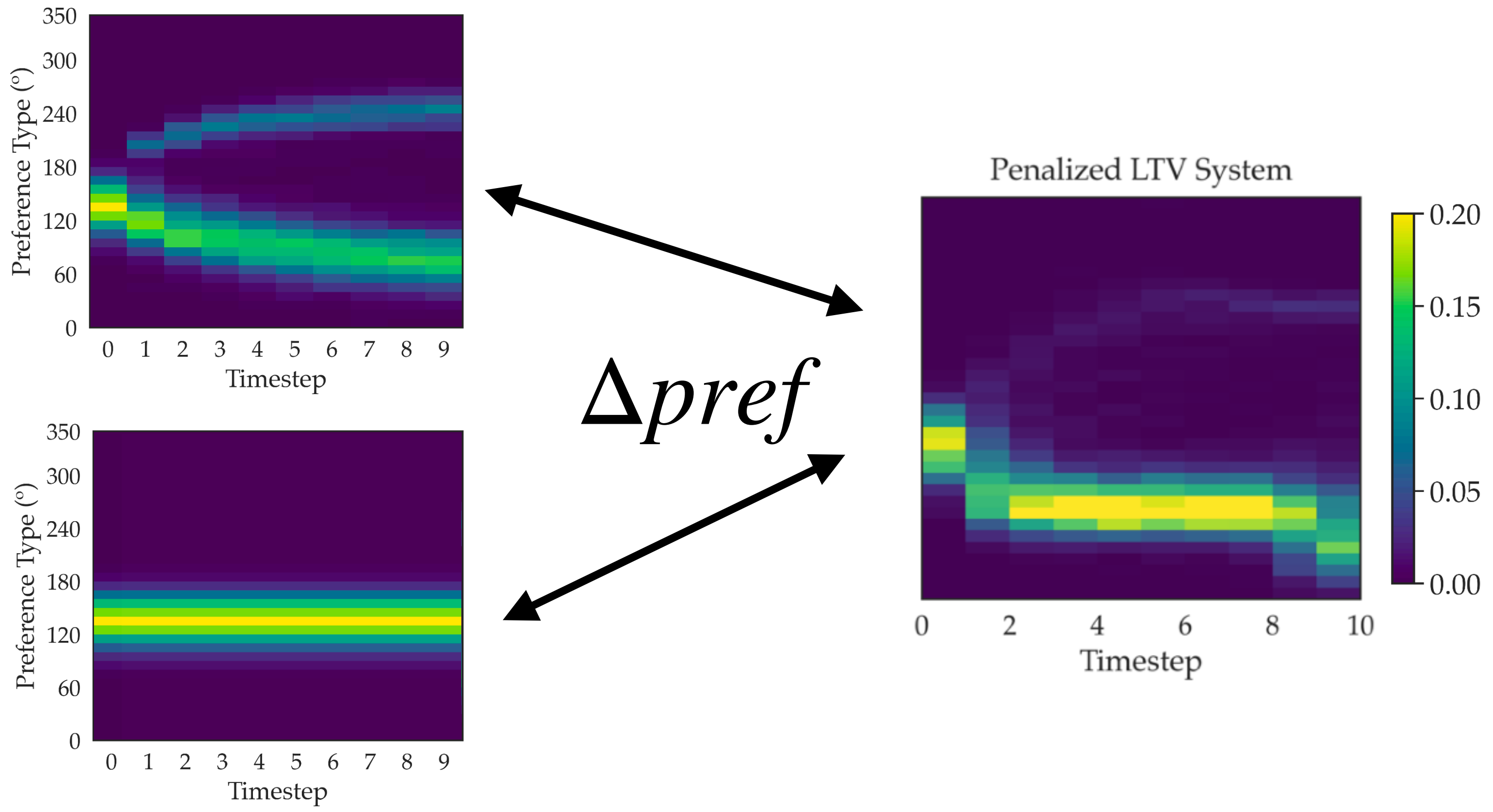
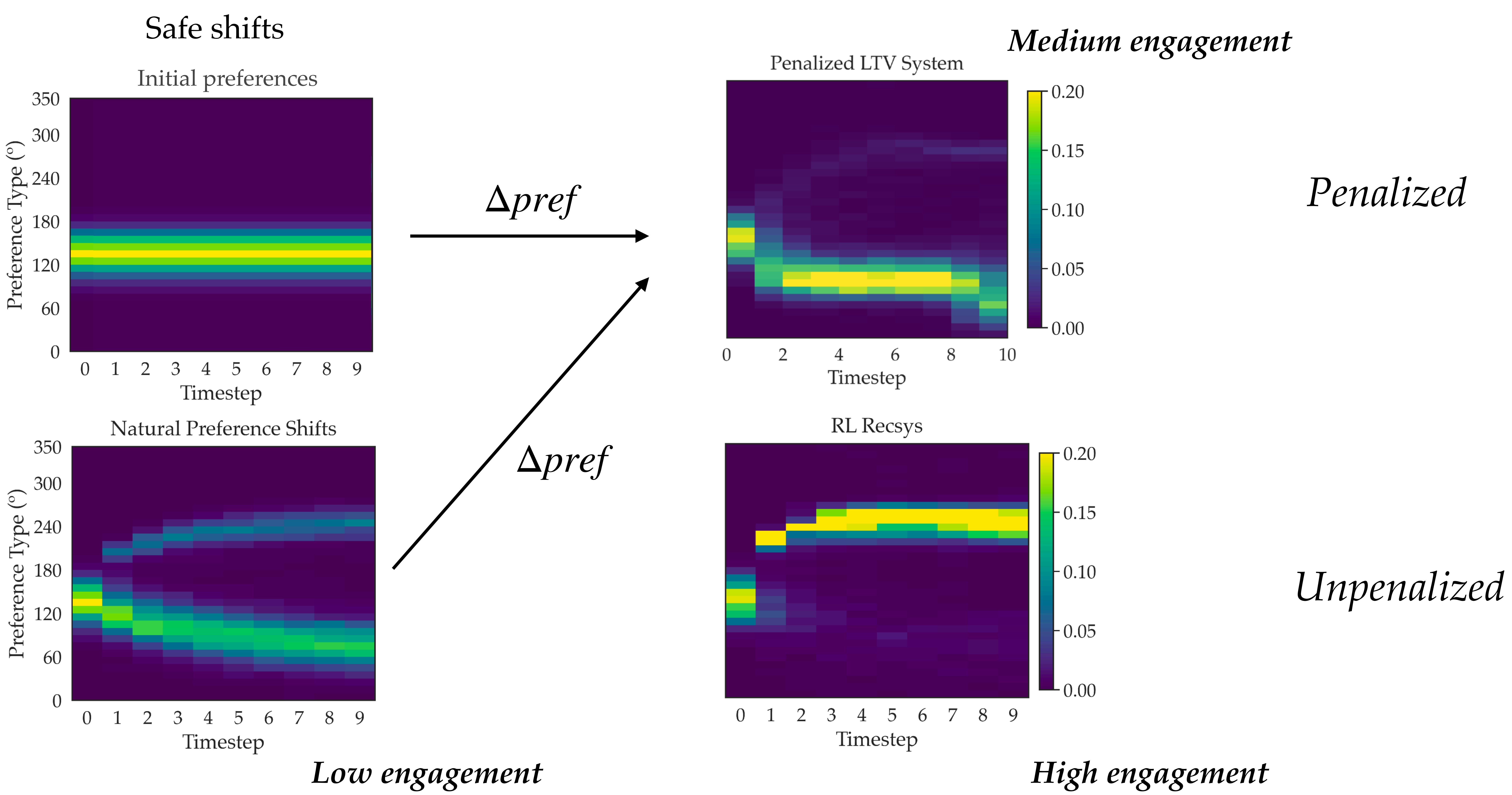


…which can be used to penalize RL training to actively avoid unwanted shifts



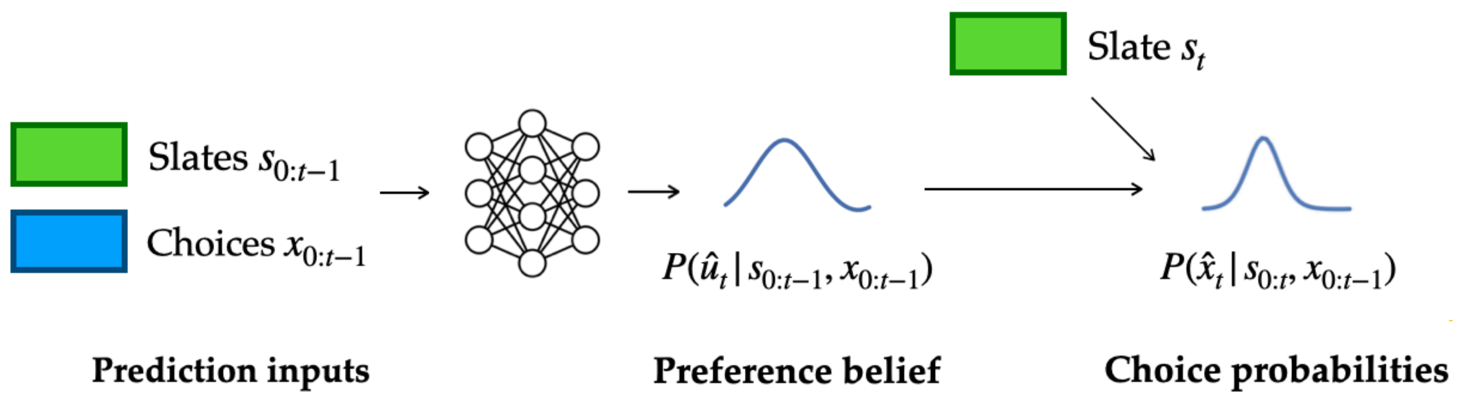
Using proxies to obtain manipulation-penalized RL system



Experiments

0. Setup

1. Method for estimating policy-induced preference shifts



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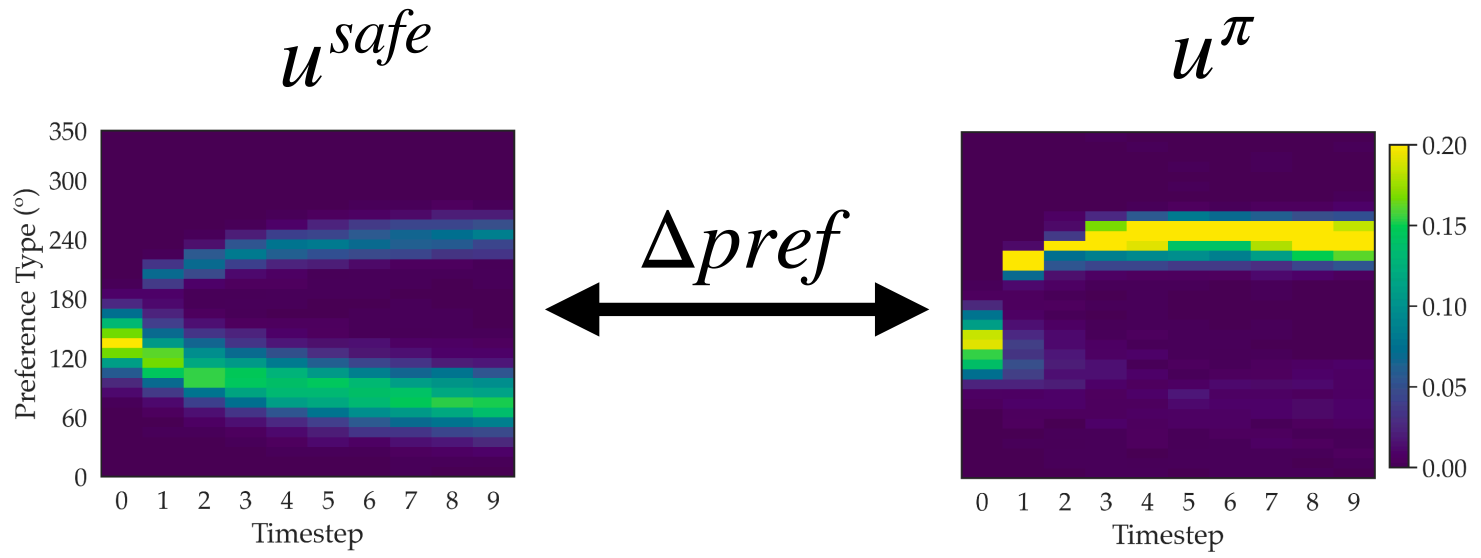

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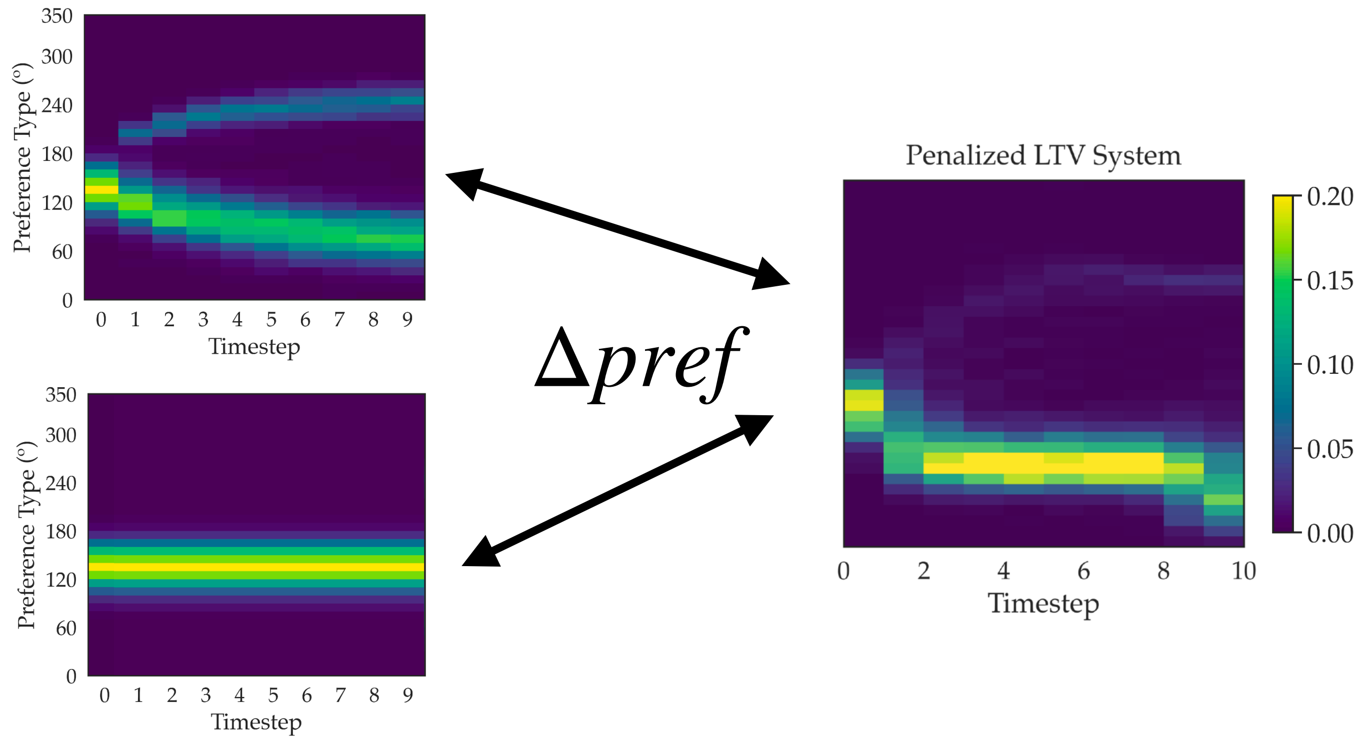
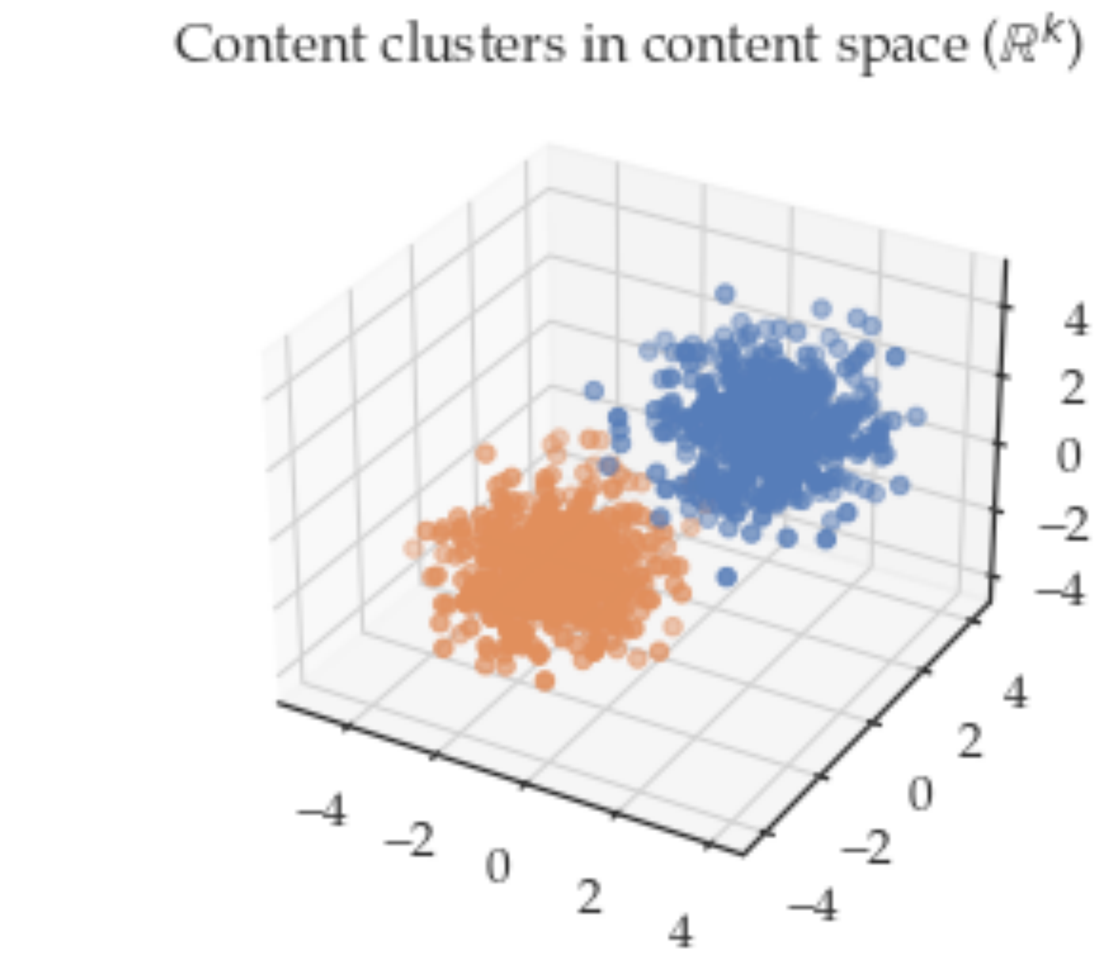
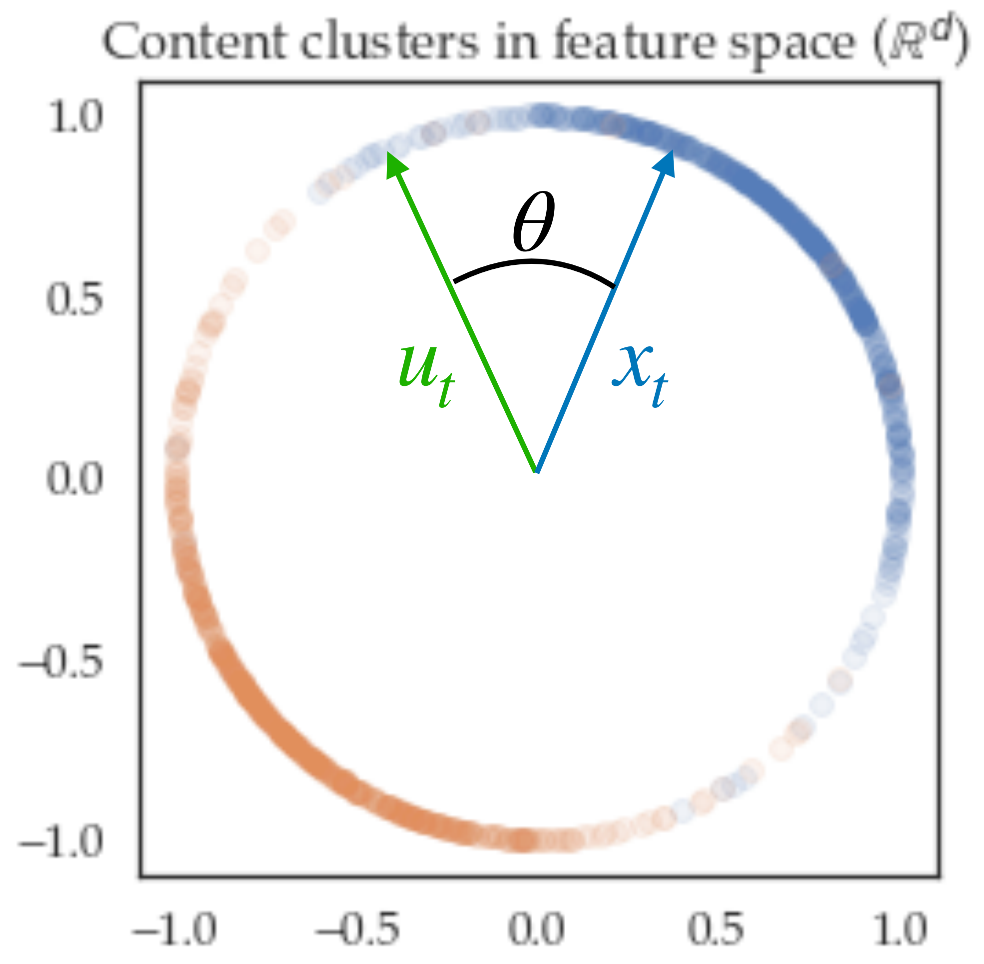
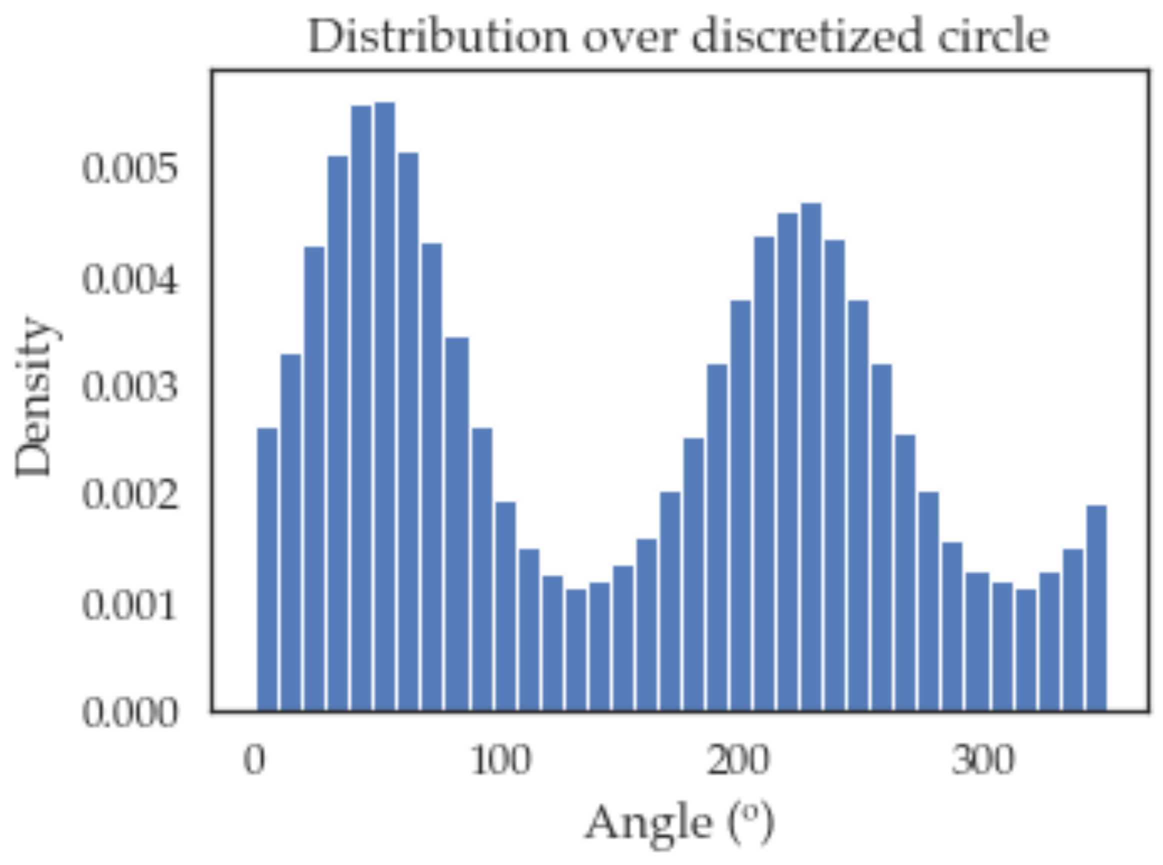


Experimental setup assumptions

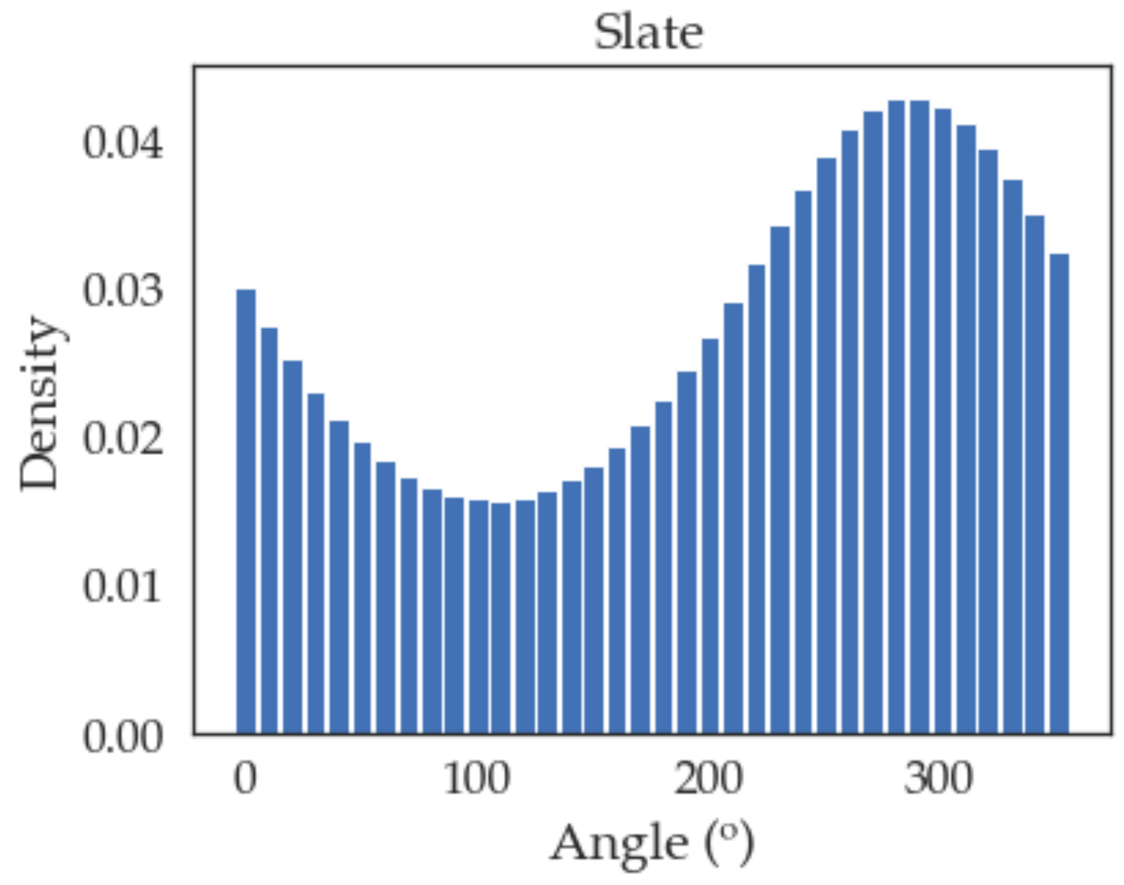




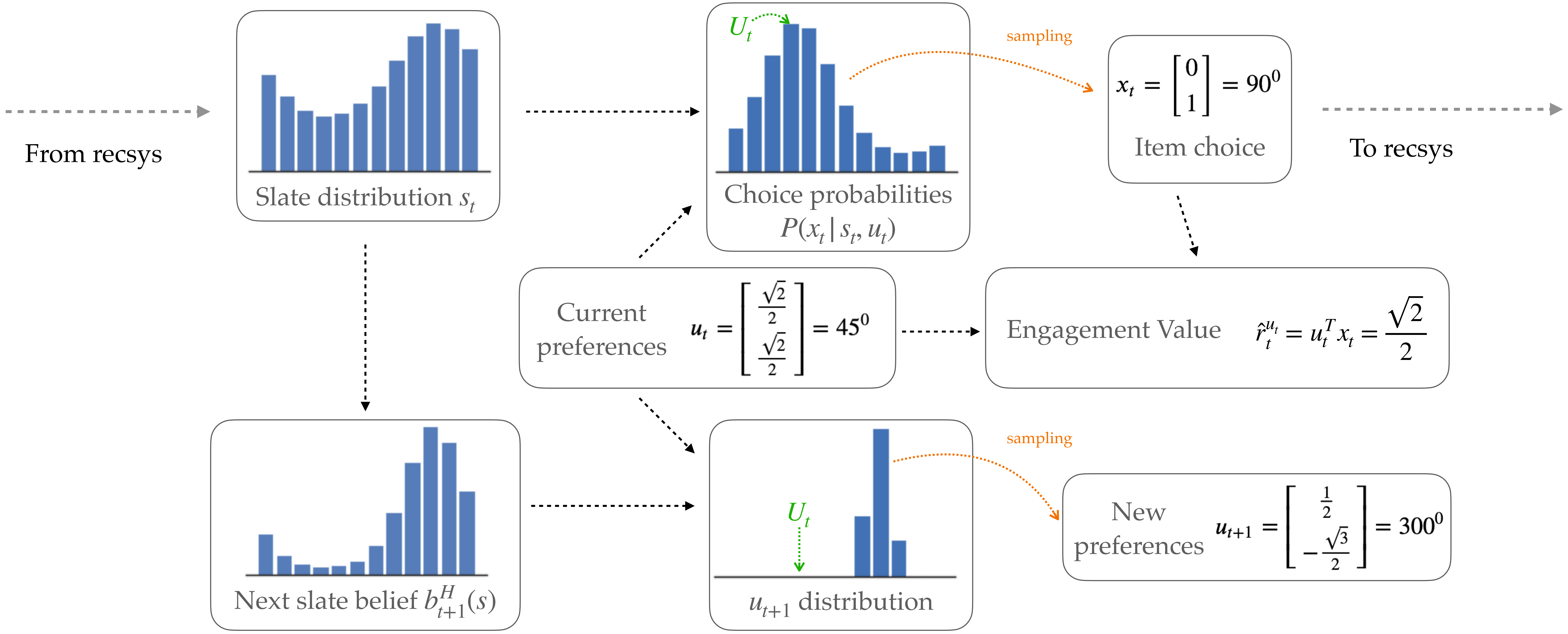
Engagement Value $\hat{r}_t^{u_t} = u_t^T x_t$



RS
subsampling



Simulated Human Model



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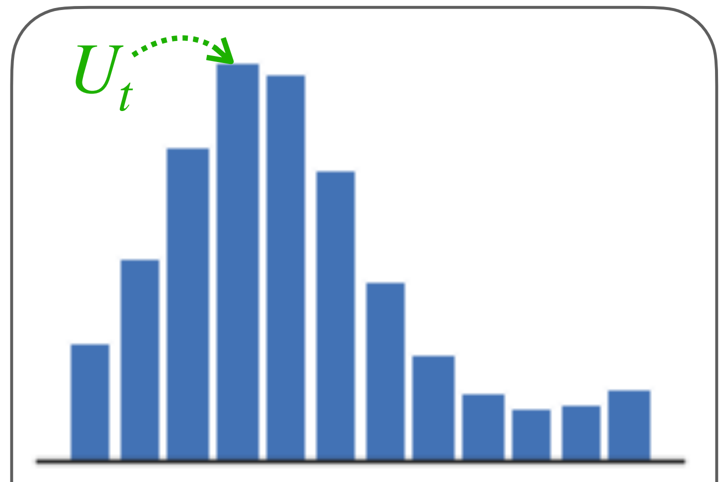
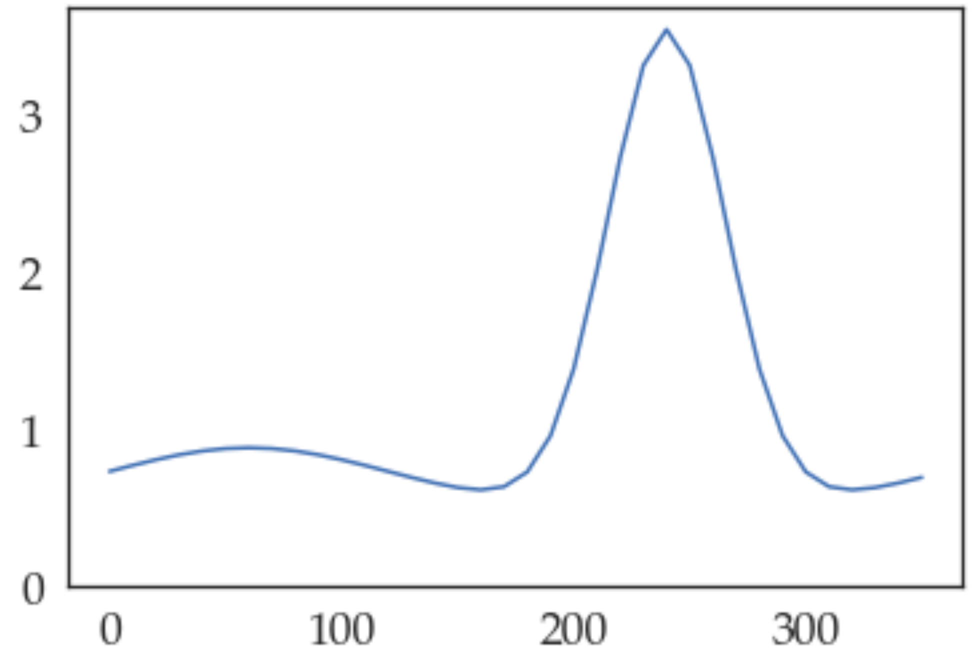
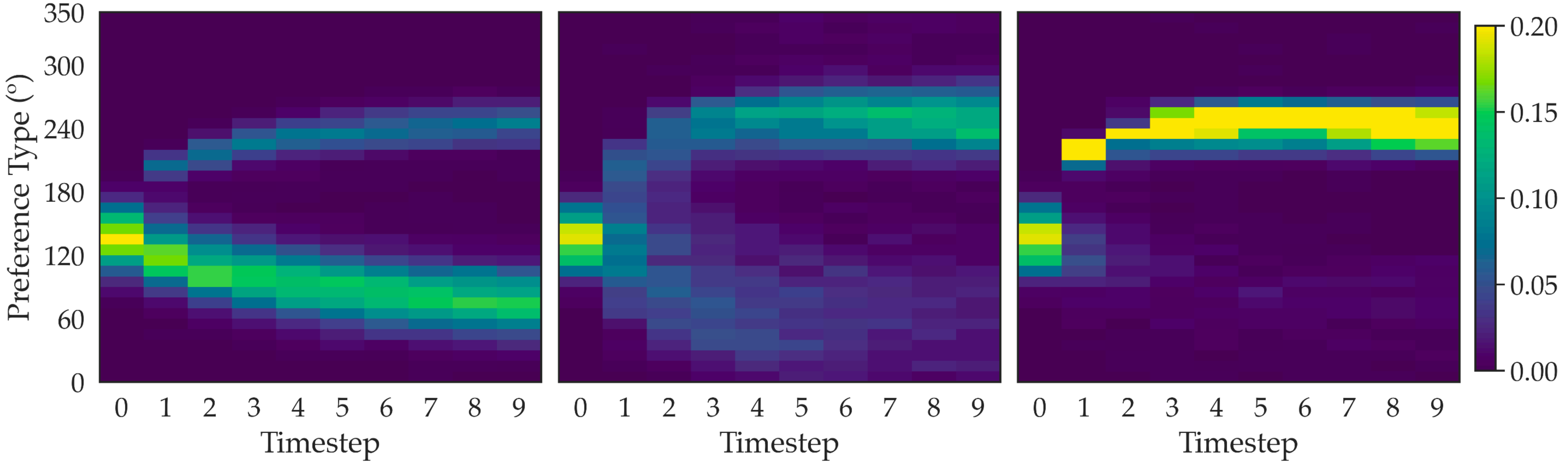


Choice probabilities
$P(x_t \mid s_t, u_t)$

Engagement Value $\hat{r}_t^{u_t} = u_t^T x_t$

$$P(x_t = x \mid s_t, u_t) = \frac{P(s_t{=}x)\, e^{\boxed{\beta_c} x^T u_t}}{\sum_x^n P(s_t{=}x)\, e^{\beta_c x^T u_t}}$$





Experiments

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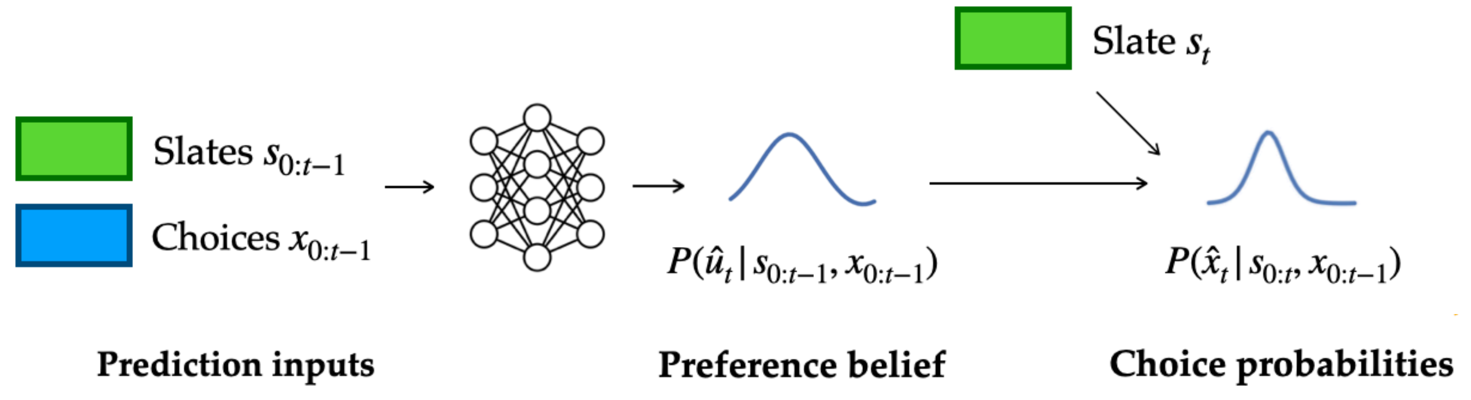

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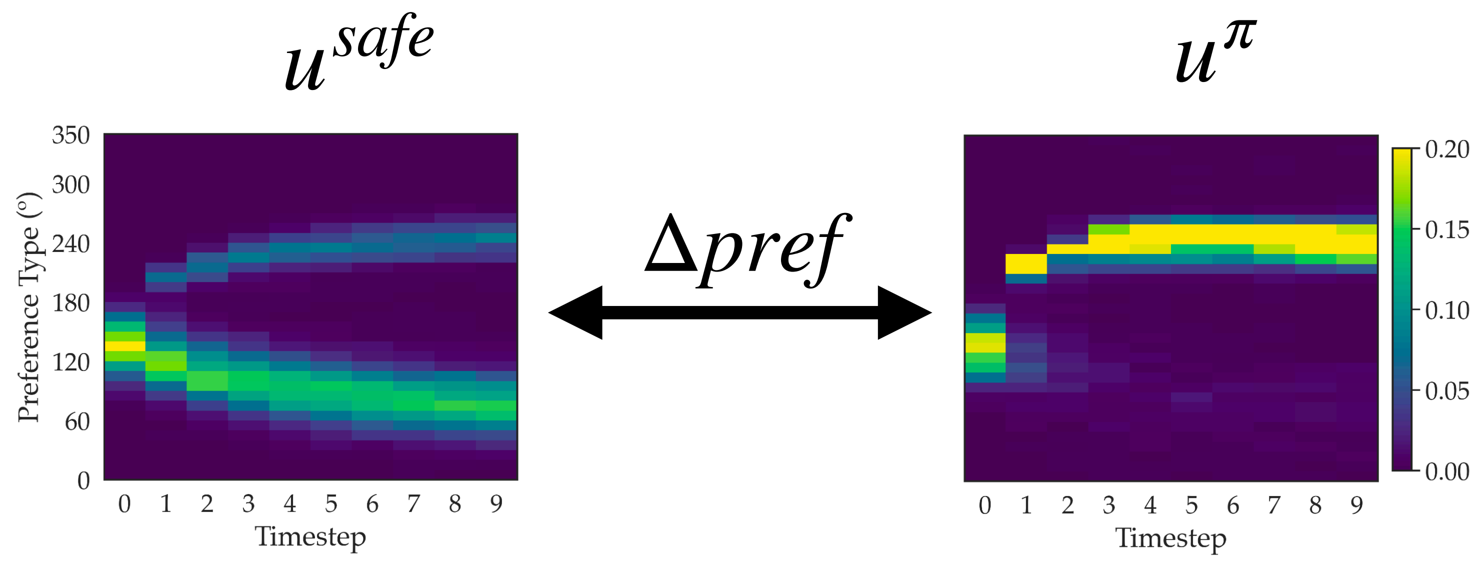
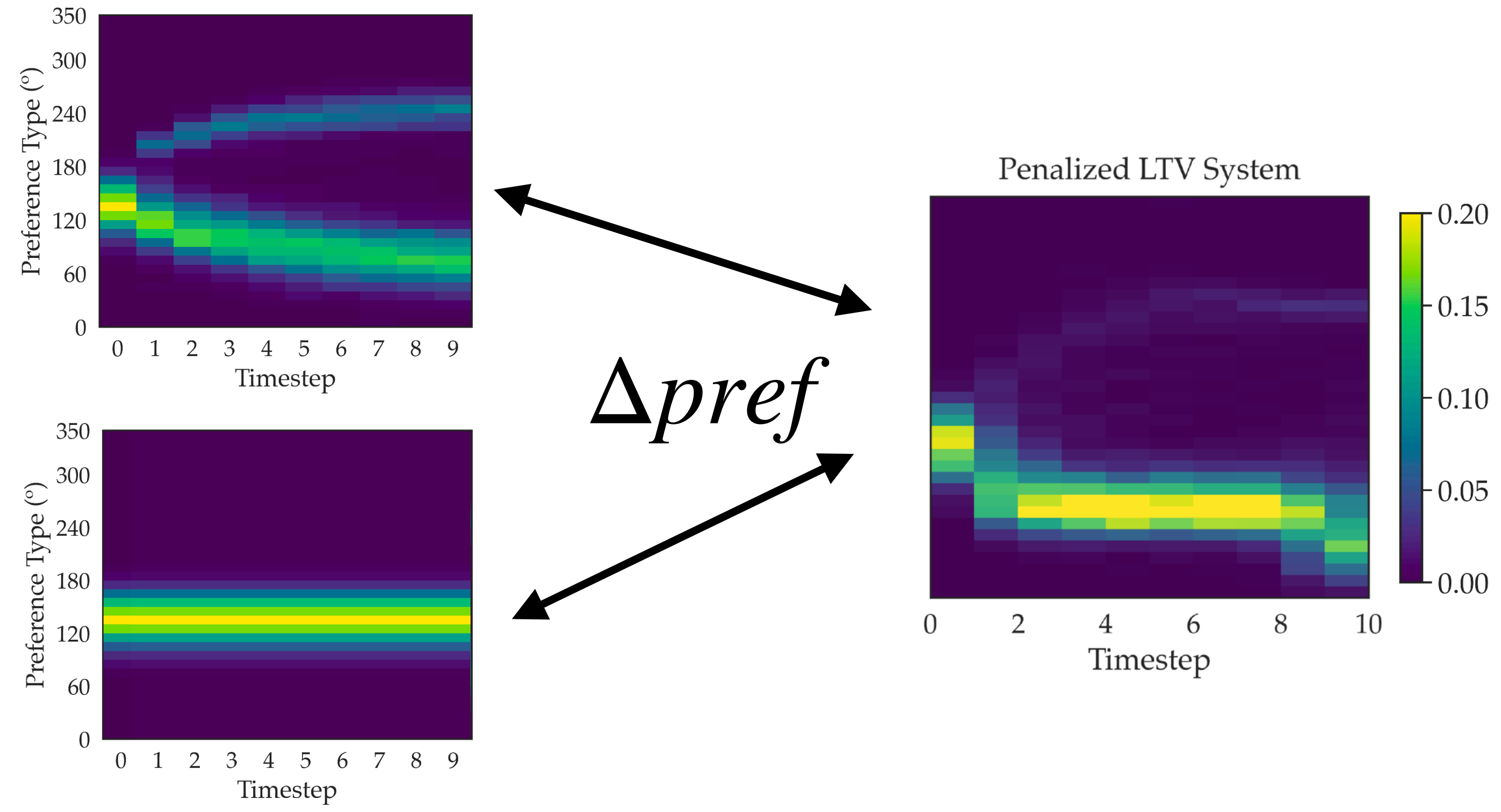
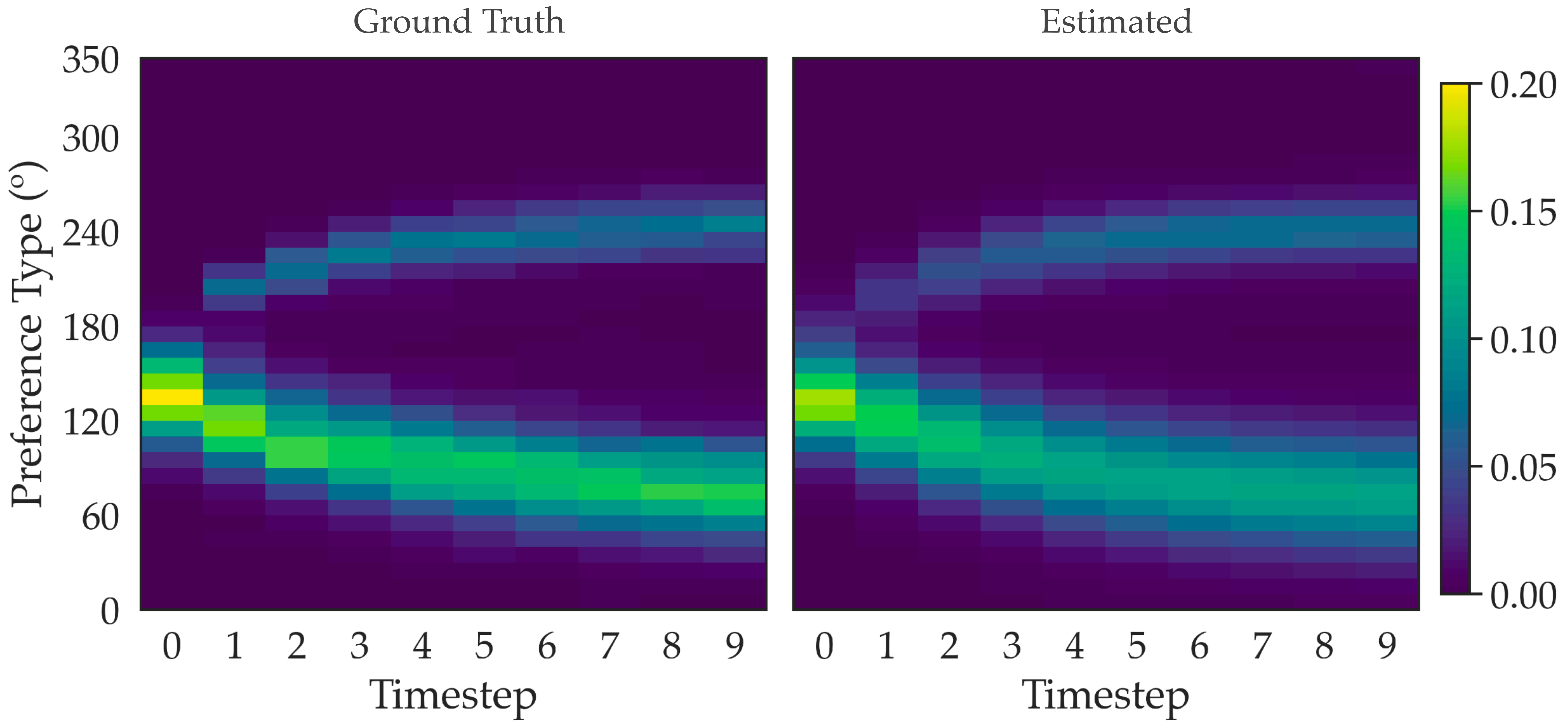


…which can be used to penalize RL training to actively avoid unwanted shifts



Estimation of policy-induced shifts

Can we predict preference shifts under never-deployed policy π' from historical data?



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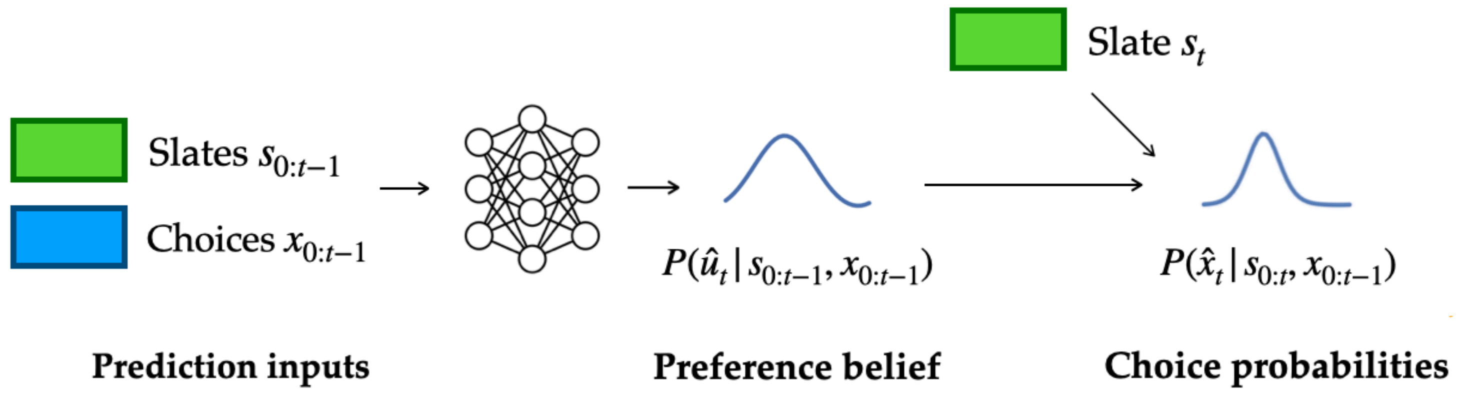

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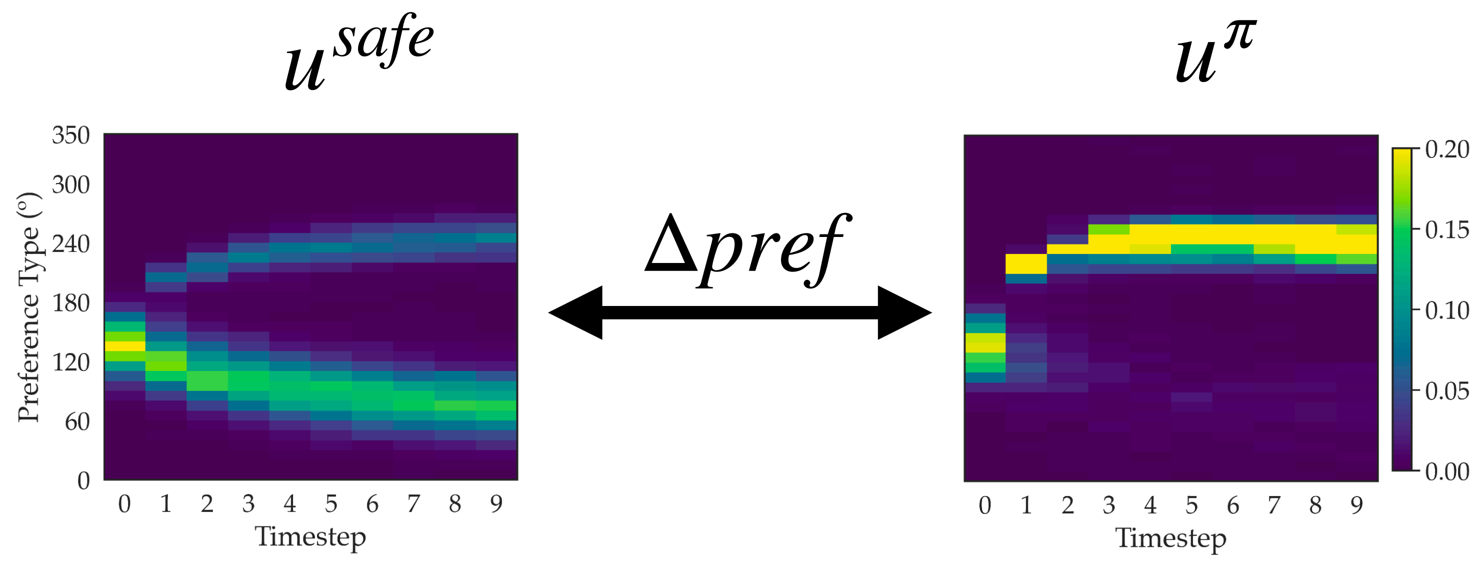
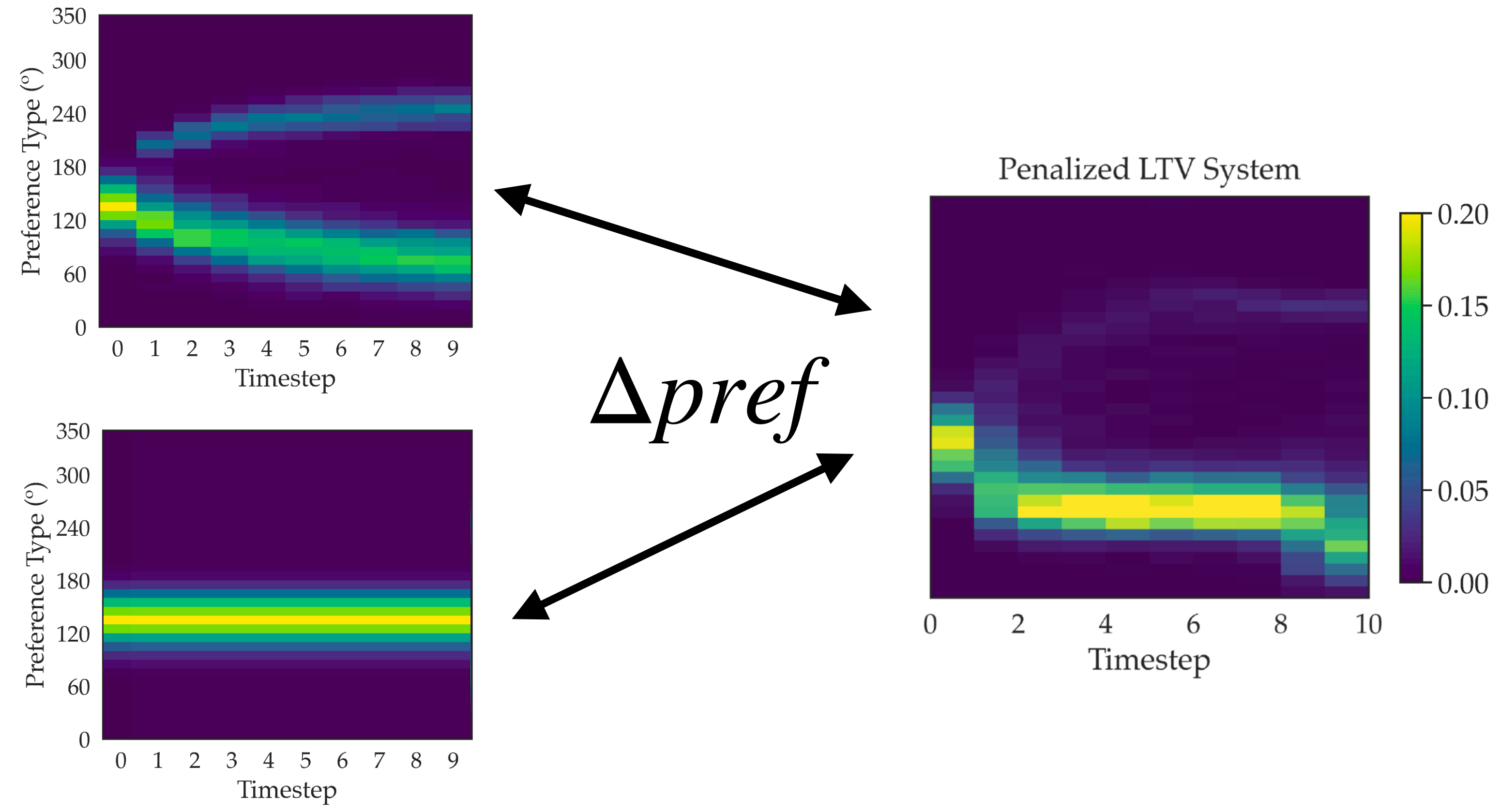
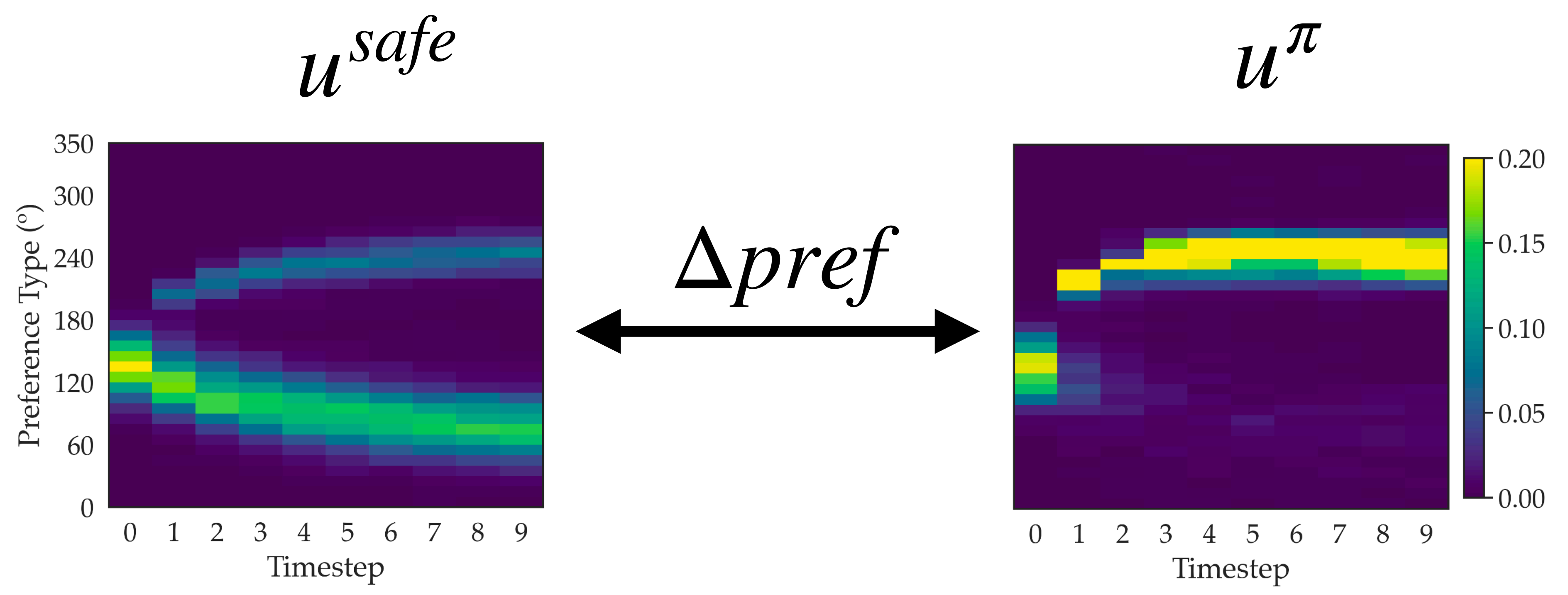




Preference distances and RL training



$$D(u^{safe}_{0:T}, u^{\pi}_{0:T}) = \sum_t \mathbb{E}\left[\hat{r}_t^{u^{safe}} - \hat{r}_t^{u^{\pi}}\right]$$

Unpenalized $\displaystyle\sum_t^T \mathbb{E}[\hat{r}_t^{u_t^{\pi}}]$

Metrics **estimated** or **computed with GT dynamics**

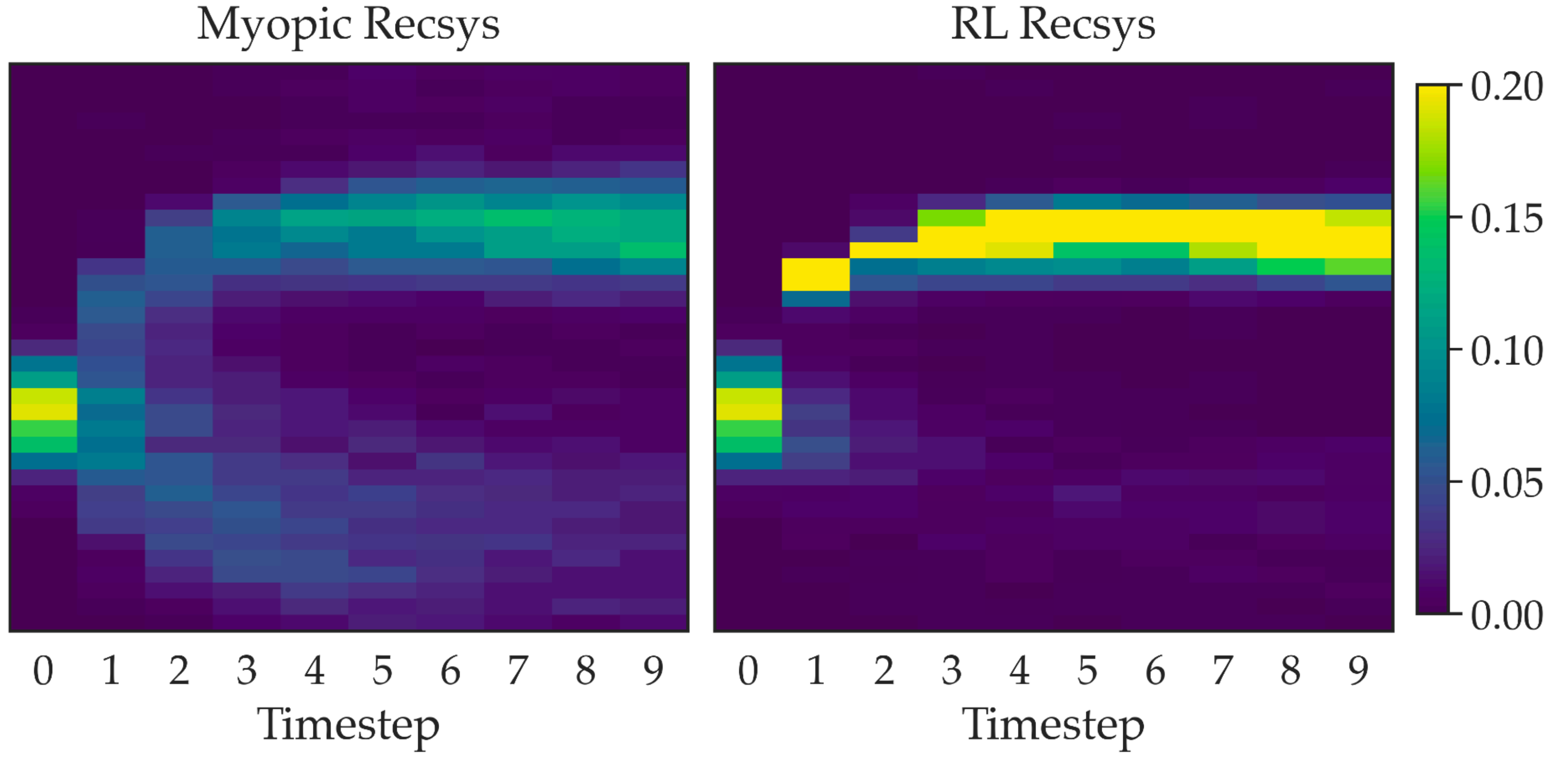
Training is with **simulated** or **on-policy** samples

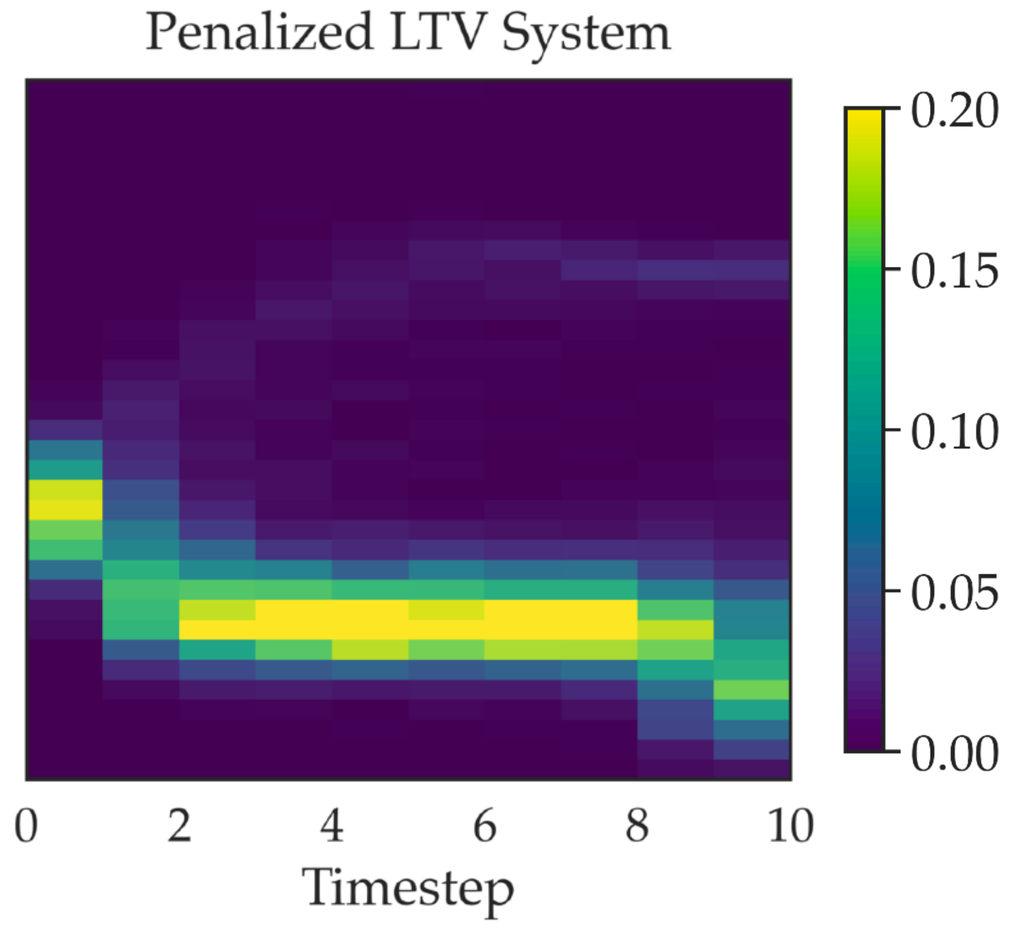
Penalized $\displaystyle\sum_t^T \mathbb{E}[\hat{r}_t^{u_t^{\pi}}] + \lambda_1 \mathbb{E}[\hat{r}_t^{u_t^{*}}] + \lambda_2 \mathbb{E}[\hat{r}_t^{u_0}]$

Results

		Oracle Training			
		Unpenalized		*Penalized*	
		Myopic	RL	Myopic	RL
Oracle Eval	$\hat{r}^{u_t^{\pi}}$	5.71	7.49	6.20	5.28
	$\hat{r}^{u_0}$	1.99	-0.08	3.61	6.21
	$\hat{r}^{u_t^*}$	2.01	-1.09	3.10	4.57
	Avg.	3.23	2.11	4.30	5.35

		Oracle Training		Training in Simulation	
		Unpen.	Penal.	Unpen.	Penal.
Oracle Eval	$\hat{r}^{u_t^{\pi}}$	7.49	5.28	6.40	5.48
	$\hat{r}^{u_0}$	-0.08	6.21	-1.24	5.61
	$\hat{r}^{u_t^*}$	-1.09	4.57	-1.83	4.43
	Avg.	2.11	5.35	1.12	5.84
Estimated E.	$\hat{r}^{u_t^{\pi}}$	5.58	5.42	6.49	5.78
	$\hat{r}^{u_0}$	1.28	5.57	-0.80	4.94
	$\hat{r}^{u_t^*}$	2.05	3.88	1.48	4.41
	Avg.	2.97	4.95	2.39	5.05





Key takeaway

in order to ethically use recommender systems at scale, we may need to take active steps to ***measure*** *and* ***penalize*** *how such systems shift users' internal states*

Thank you!