Explicit vs. Implicit Modeling of Human Internal State for Robot Planning

Arvind Rajaraman, Ran (Thomas) Tian, Anca Dragan, Andrea Bajcsy

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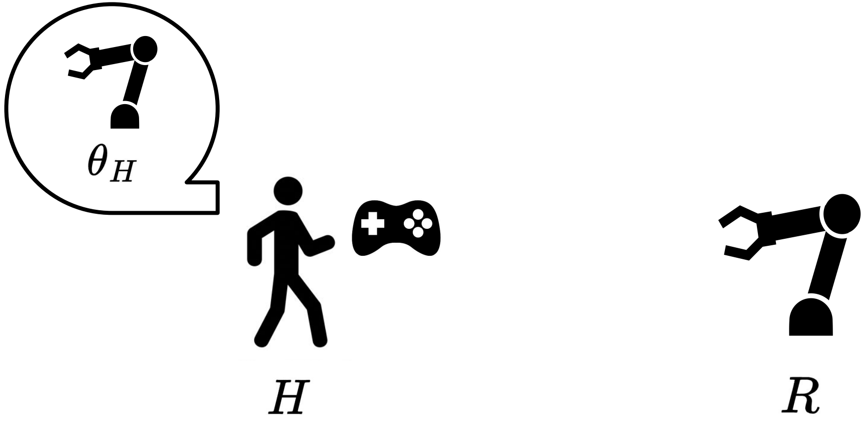
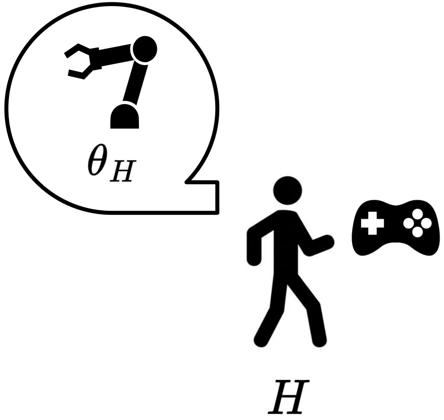
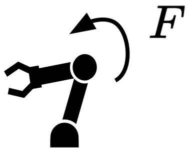

θ_H
H
R

Humans have internal models of reality

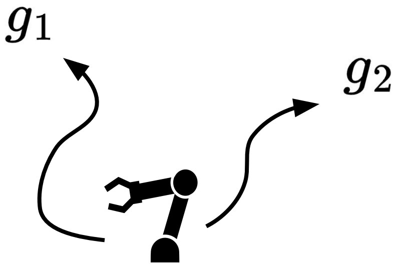
θ_H = aspect of task that human is unsure about but continuously learns about.



Examples:

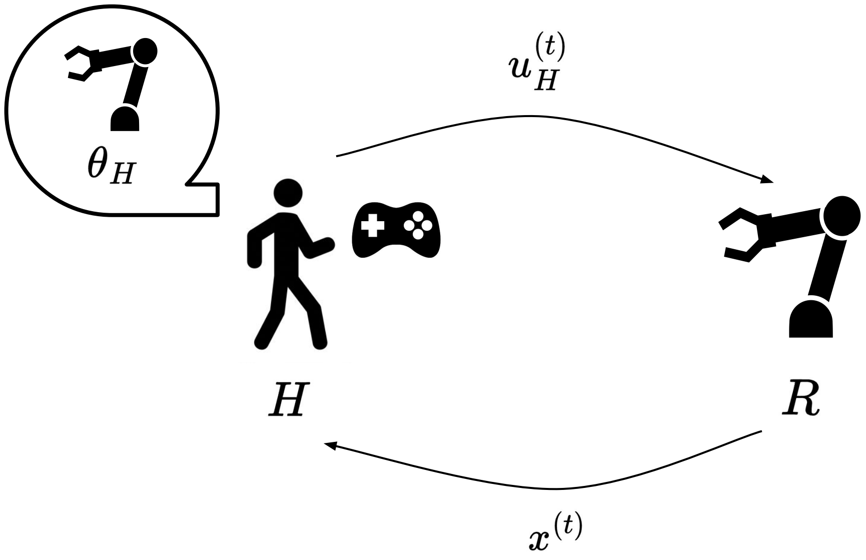


Robot's physical properties



Human's goal preference

Problem: Human models may be misaligned with reality

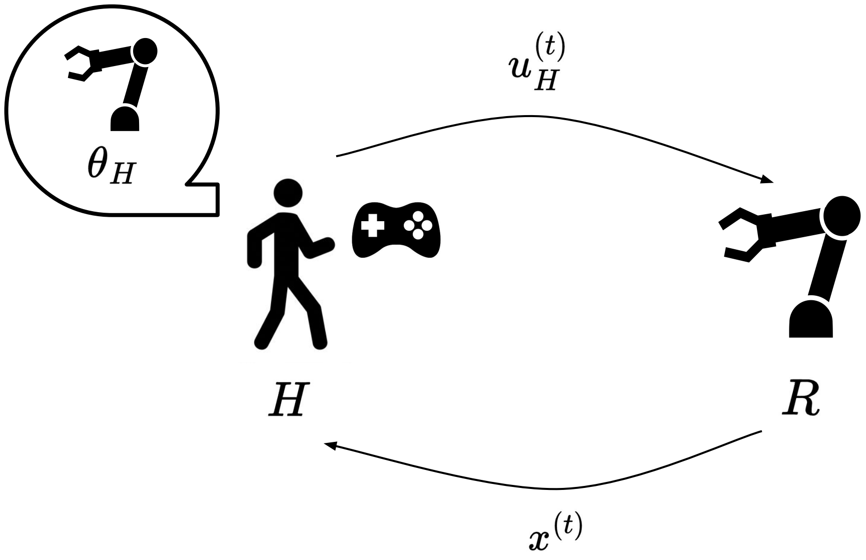


e.g. θ = joint friction

$$\theta^{(1)} = 0.2$$

$$\theta_H^{(1)} = 3.0$$

Problem: Human models may be misaligned with reality

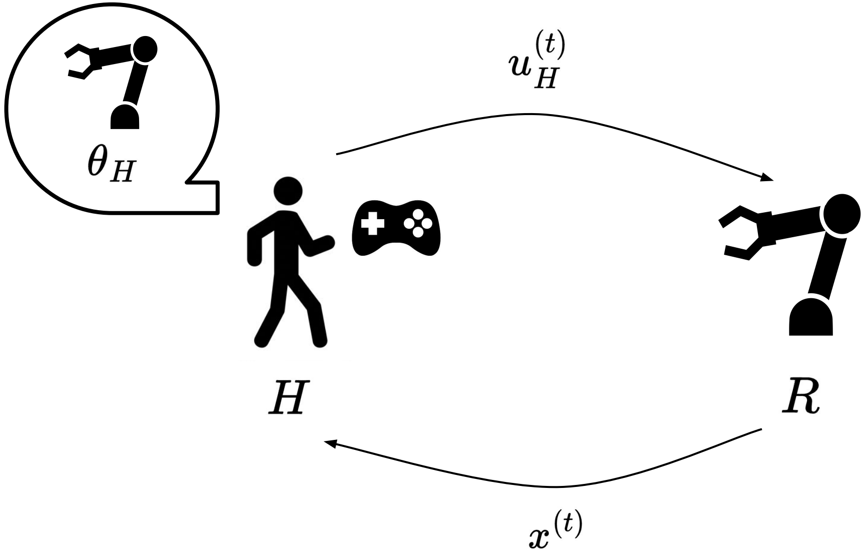


e.g. θ = joint friction

$$\theta^{(2)} = 0.4$$

$$\theta_H^{(2)} = 2.7$$

Problem: Human models may be misaligned with reality

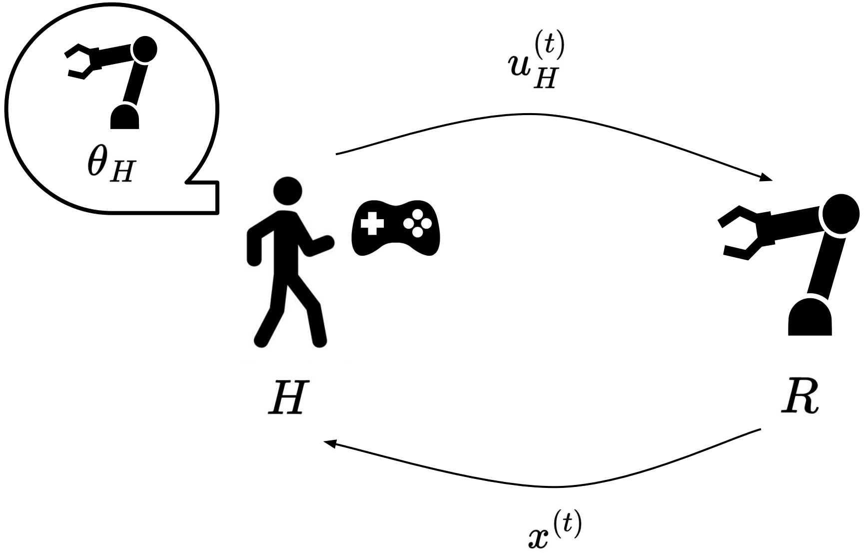


e.g. θ = joint friction

$$\theta^{(\cdots)} = \cdots$$

$$\theta_H^{(\cdots)} = \cdots$$

Problem: Human models may be misaligned with reality

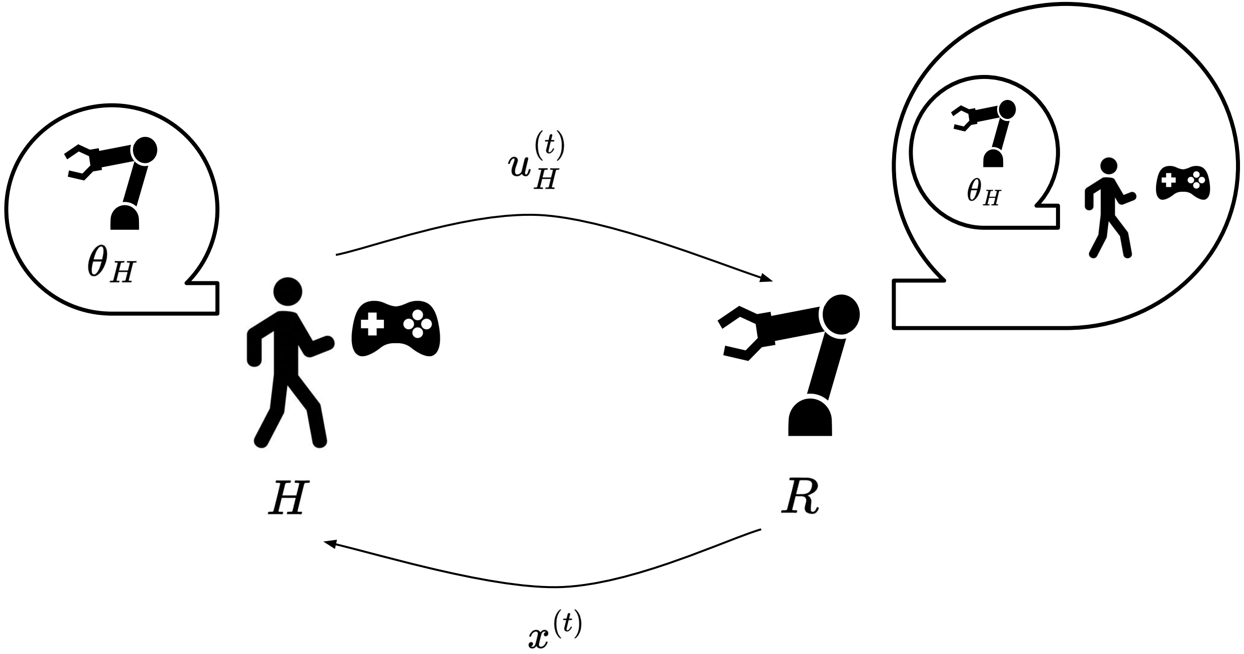


e.g. θ = joint friction

$$\theta^{(1000)} = 3.2$$

$$\theta_H^{(1000)} = 3.1$$

Solution: Robotic influence!



Prior Work: Inferring the dynamics of human learning

Learn human dynamics

$$\theta_H^{(t+1)} = f_D(\theta_H^{(t)}, x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

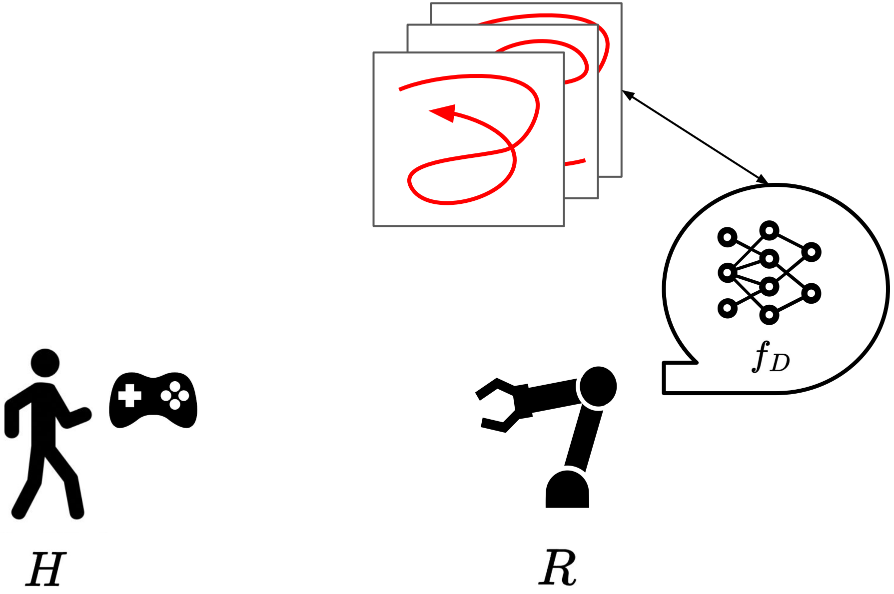
learned averaged dynamics model

Robotic influence

$$\pi_R(x^{(t)}, \theta_H^{(t)} \mid f_D)$$

Towards Modeling and Influencing the Dynamics
of Human Learning (Tian et al., HRI 2023)

Prior Work: Inferring the dynamics of human learning



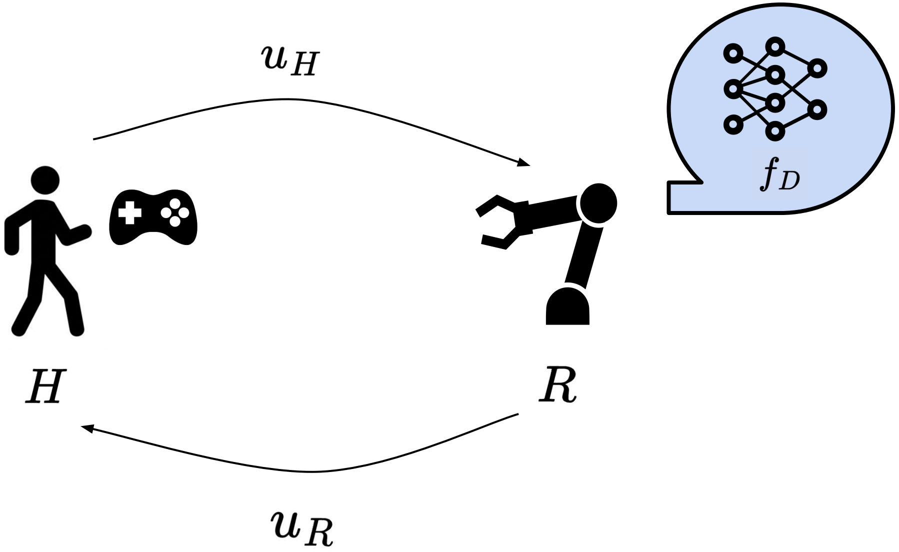
Dynamics of human learning

$$\theta_H^{(t+1)} = f_D(\theta_H^{(t)}, x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

Robotic influence

$$\pi_R(x^{(t)}, \theta_H^{(t)} \mid f_D)$$

Prior Work: Inferring the dynamics of human learning



Dynamics of human learning

$$\theta_H^{(t+1)} = f_D(\theta_H^{(t)}, x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

Robotic influence

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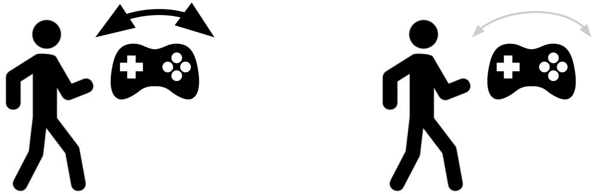
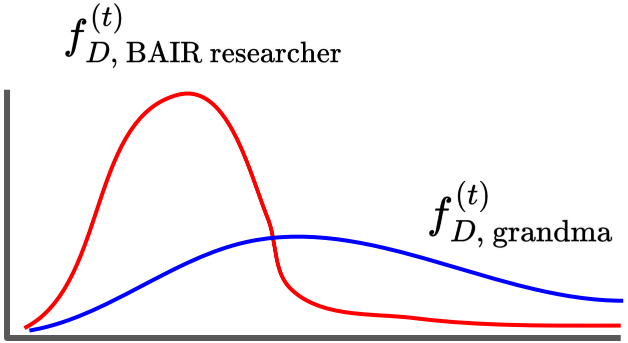
Challenges with averaged learning dynamics



Humans learn
differently



Distribution shift

Previous solution: global robotic influence

Learn *global* human dynamics

$$\theta_H^{(t+1)} = f_D(\theta_H^{(t)}, x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

Proposed approach: Personalized robotic influence

~~**Learn *global* human dynamics**~~

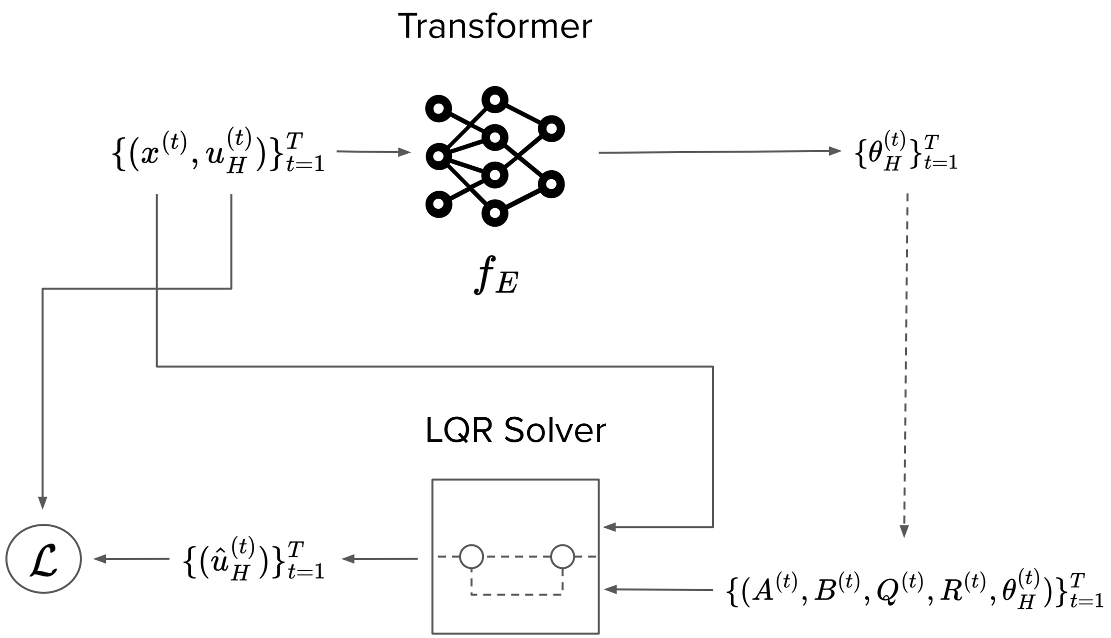
$$\cancel{\theta_H^{(t+1)} = f_D(\theta_H^{(t)}, x^{(t)}, u_H^{(t)}, u_R^{(t)})}$$

Learn *personalized* estimator of human internal state

$$\theta_H^{(t)} = f_E(x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

Learning Latent Representations to Influence
Multi-Agent Interaction (Xie et al., CoRL 2020)

Internal state estimation: Training details



Estimation of internal state

$$\theta_H^{(t)} = f_E(x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

Robotic influence

$$\pi_R(x^{(t)}, \theta_H^{(t)} \mid f_E)$$

Internal state estimation and influence is closed-loop

Estimation of internal state

$$\theta_H^{(t)} = f_E(x^{(t)}, u_H^{(t)}, u_R^{(t)})$$

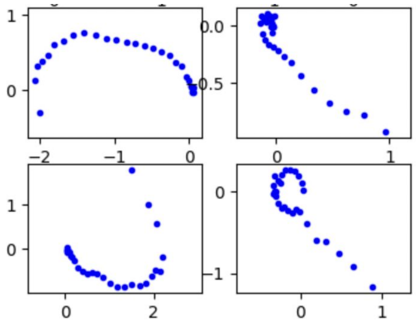
Robotic influence

$$\pi_R(x^{(t)}, \theta_H^{(t)} \mid f_E)$$

Preliminary results

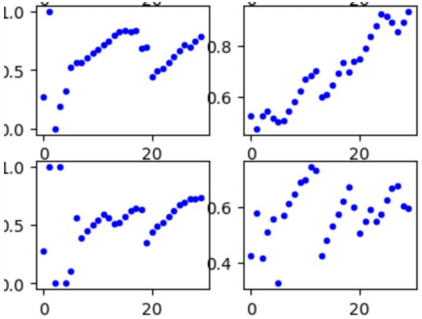
Trajectories

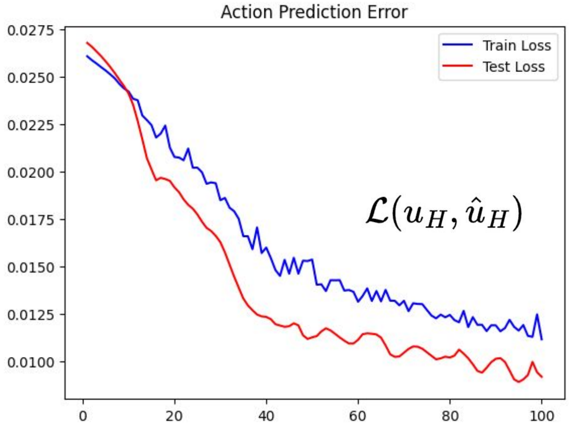
$$\{(x^{(t)}, u_H^{(t)})\}_{t=1}^{T}$$

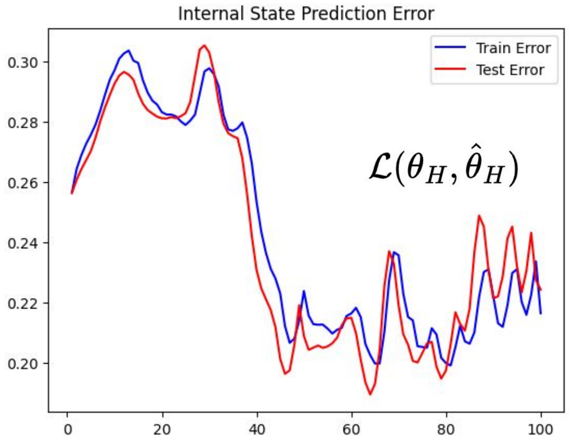


Internal States

$$\{\theta_H^{(t)}\}_{t=1}^{T}$$







Thank you!

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