Measuring State Utilization During Decision Making in Human-Robot Teams

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INTRODUCTION

In human robot teams, robots need to adapt to human external states (such as position and velocity) and internal states (such as workload and fatigue)

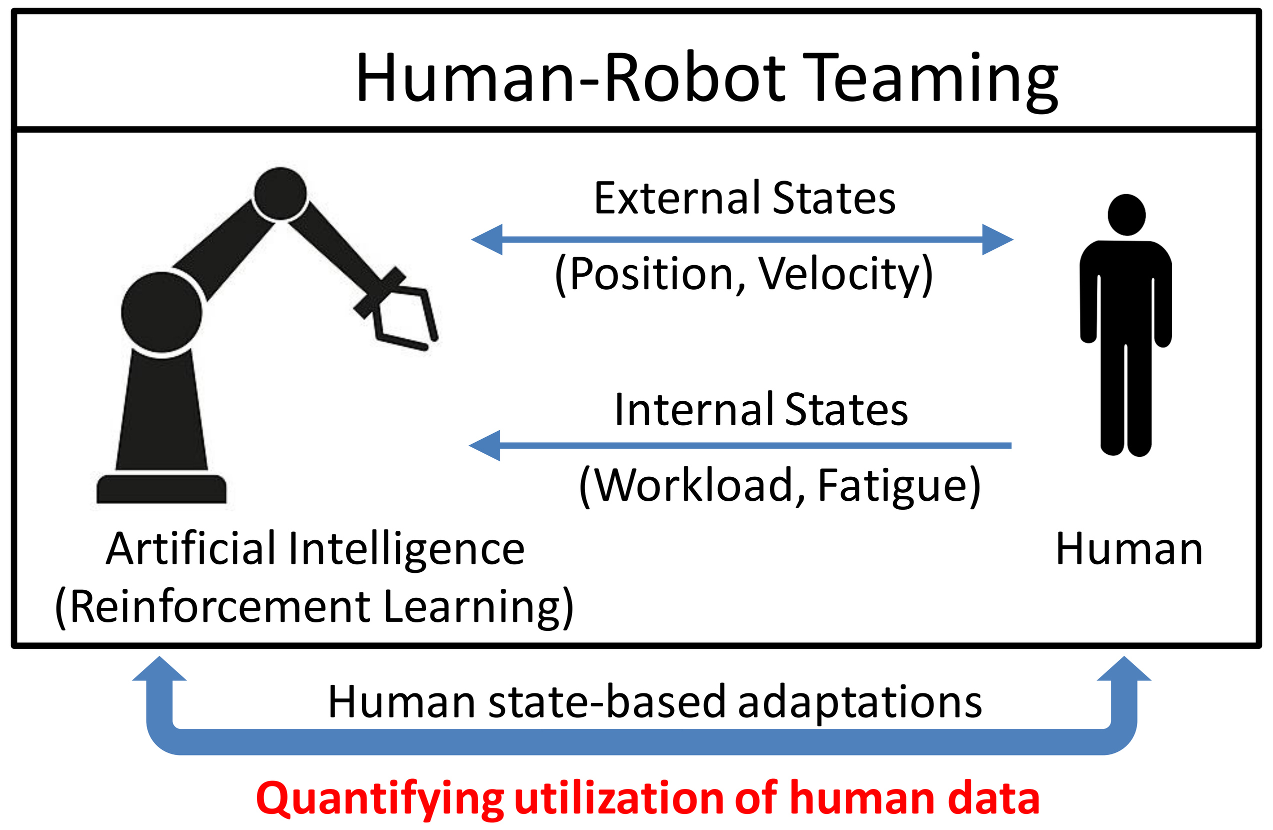


Figure 1: State utilization to quantify utilization of human data by a robot

Problem: How much are adaptive black-box algorithms such as reinforcement learning algorithms relying on human data?

Proposed solution: New state utilization metric that quantifies RL agent's reliance on state features, including human data in human robot teaming scenarios.

Tests:

- Cartpole by OpenAI Gym (Toy Problem)
- NASA MATB-II (Human Subjects Study)

Observed Benefit: Metric indeed increases explainability in multimodal neural networks. Significant potential impact in multimodal data fusion across various application

METHOD

- Observe the difference between output of the decision network with original dataset and permuted dataset.
- A smaller change implies the state feature S_{ni} have low utilization and vice versa.

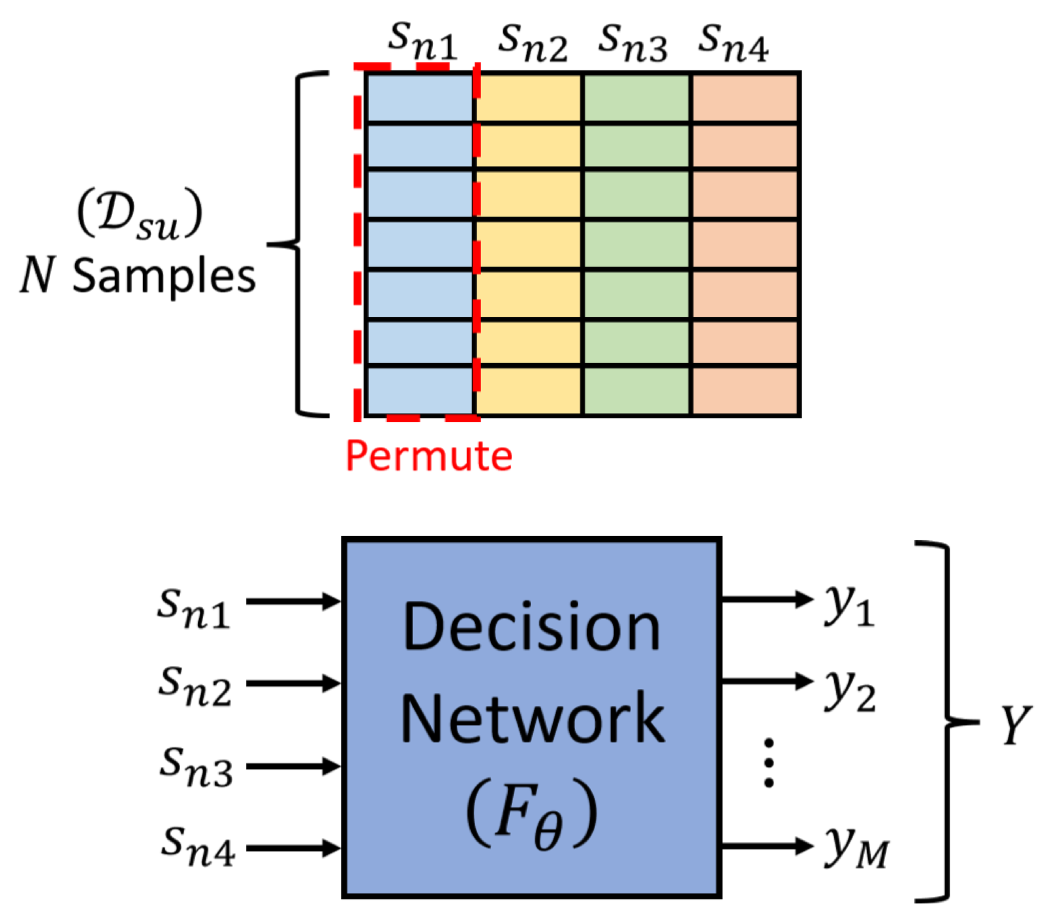
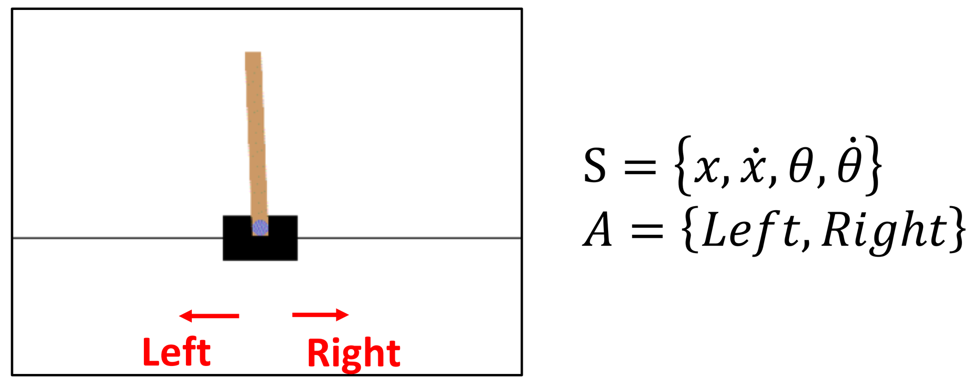


Figure 2: Permuting/shuffling samples of a state feature S_{ni} in the replay buffer to break the association between the state feature S_{ni} and the output Q

Algorithm 1: State Utilization for RL

Initialize the RL decision network F_θ, learned model parameters θ, replay memory $\mathcal{D}_{replay}$;
Sample a batch of data $\mathcal{D}_{su}$ from replay memory $\mathcal{D}_{replay}$;
Compute decision network output Y, Eq. 2;
for *each state feature s_{ni}* **do**
  Randomly permute the samples of state feature s_{ni} while keeping the state features s_{nj}, $j \neq i$ unchanged;
  Compute decision network output Y_i with permuted state feature s_{ni}, Eq. 3;
end
for *each state feature s_i* **do**
  Compute State Utilization (SU_i) using $SU_i = \frac{\|Y_i - Y\|}{\sum_{j=1}^{S} \|Y_j - Y\|}$, Eq. 4;
end

ABLATION STUDIES ON CARTPOLE



$S = \{x, \dot{x}, \theta, \dot{\theta}\}$
$A = \{Left, Right\}$

Figure 3: Cartpole Environment by OpenAI Gym

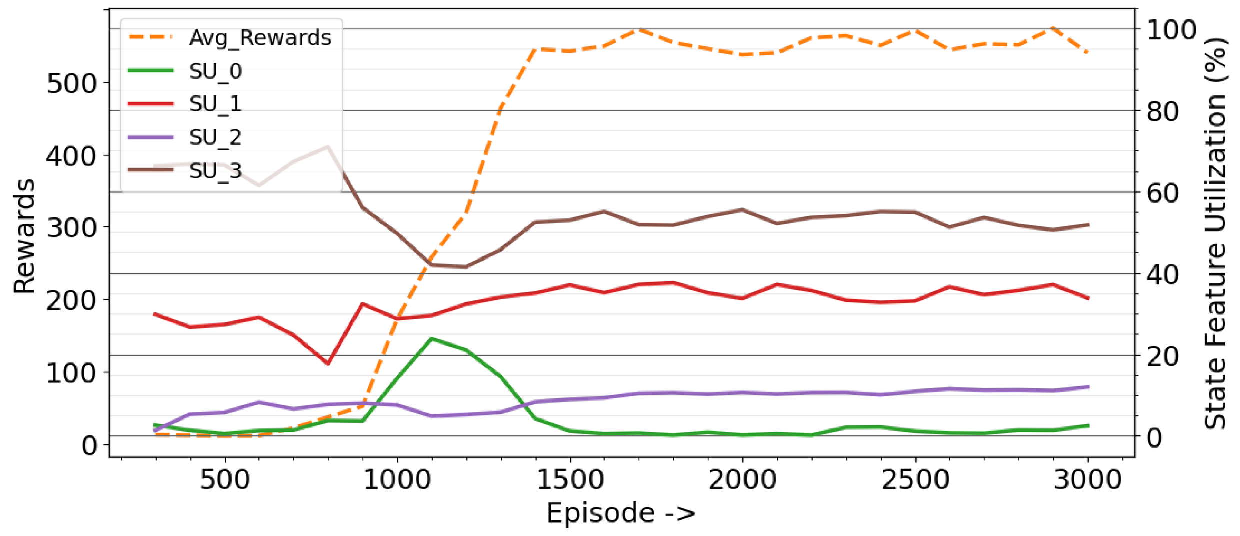


Figure 4: Average Rewards and State Utilization (SU) across episodes for the Cartpole environment solved by a DDQN agent with $S = \{x, \dot{x}, \theta, \dot{\theta}\}$.

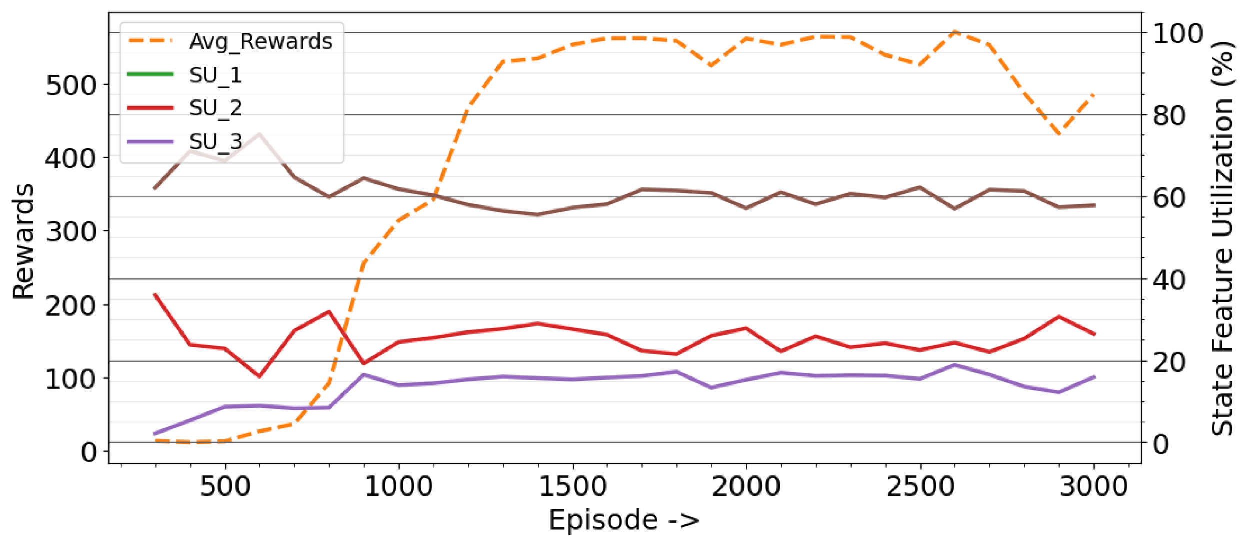


Figure 5: Average Rewards and State Utilization (SU) across episodes for the Cartpole environment without S_{n0} i.e., $S = \{\cancel{x}, \dot{x}, \theta, \dot{\theta}\}$.

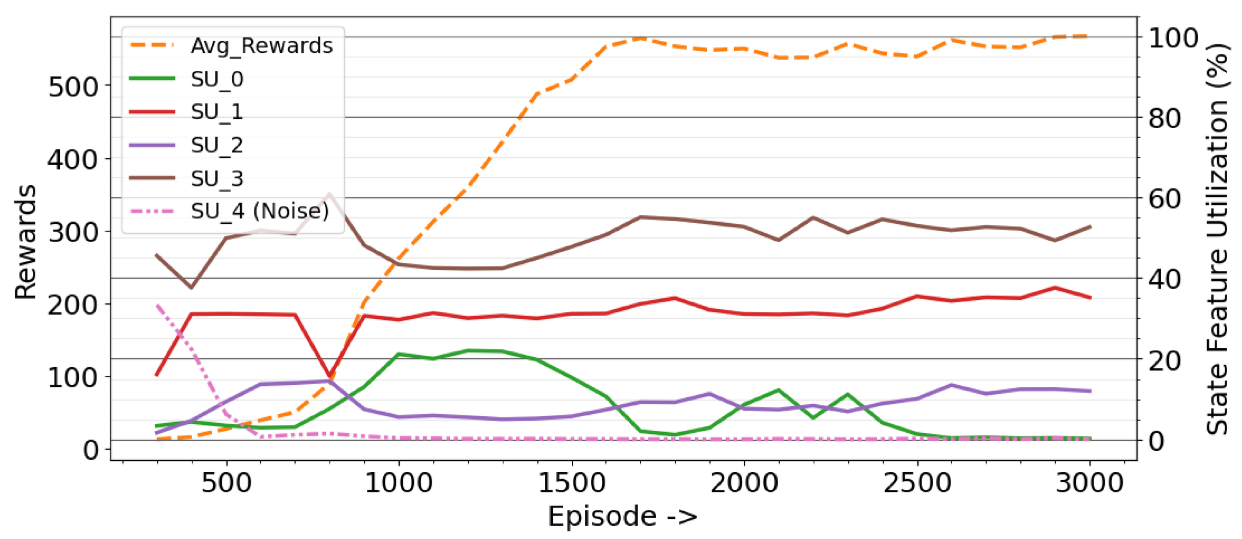


Figure 6: Average Rewards and State Utilization (SU) across episodes for the Cartpole environment with a random noise state feature (S_{n4}), i.e., $S = \{x, \dot{x}, \theta, \dot{\theta}, Noise\}$.

MEASURING UTILIZATION OF HUMAN DATA IN HUMAN ROBOT TEAMING

- SU computed in prior human-robot studies [3][4] showed the RL agent's dependence on human input.

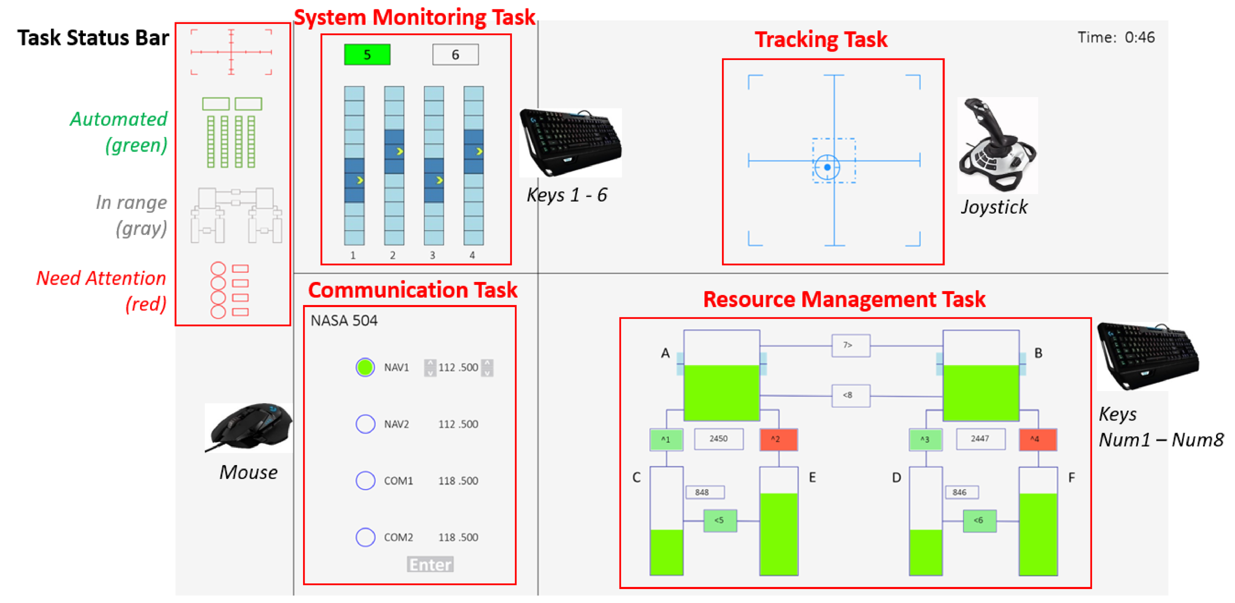


Figure 7: The NASA Multi-Attribute Task Battery-II Env.

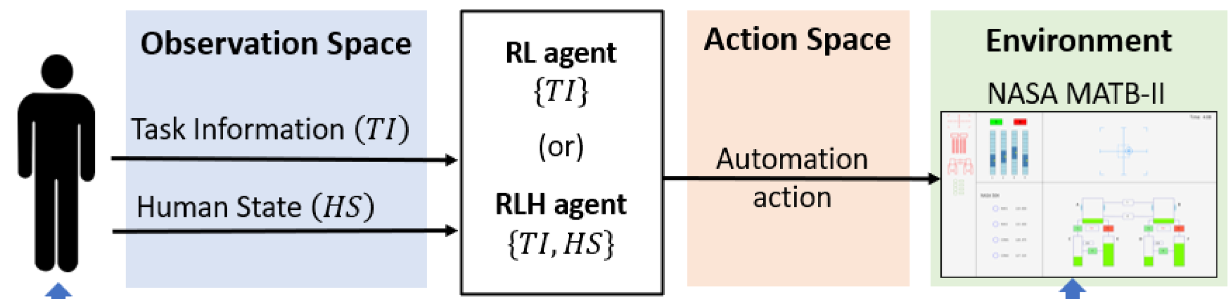


Figure 3: Adaptive Human-Robot Teaming architecture with human state estimates augmented to RL's observation space.

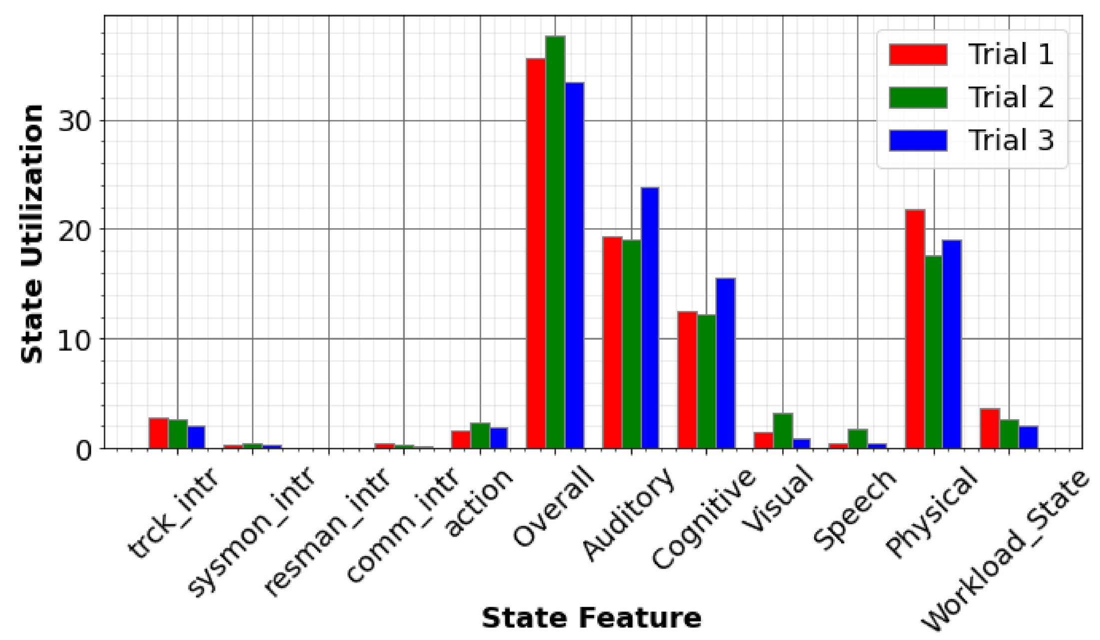


Figure 8: State Utilization for the RLH agent trained on task interaction and human internal states data in the NASA MATB-II experiment.

CONTACT INFORMATION

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[2] S. Singh, P. P. Markopoulos, E. Saber, J. D. Lew and J. Heard, "Measuring Modality Utilization in Multi-Modal Neural Networks," *2023 IEEE Conference on Artificial Intelligence (CAI)*, Santa Clara, CA, USA, 2023, pp. 11-14.
[3] S. Singh and J. Heard, "A Human-Aware Decision Making System for Human-Robot Teams," 2022 17th Annual System of Systems Engineering Conference (SOSE), 2022, pp. 268-273.
[4] S. Singh and J. Heard, "Human-aware reinforcement learning for adaptive human robot teaming," in Proceedings of the 2022 ACM/IEEE International Conference on Human-Robot Interaction, ser. HRI '22. IEEE Press, 2022, p. 1049–1052.