



Action Robust Reinforcement Learning and Applications in Continuous Control

Chen Tessler*, Yonathan Efroni* and Shie Mannor

*equal contribution

Poster #272



Robust MDPs

$$\pi^* = \arg \max_{\pi} \min_{P \in \{P_1, \dots, P_n\}} \mathbb{E}_P \left[\sum_t \gamma^t r_t \right]$$

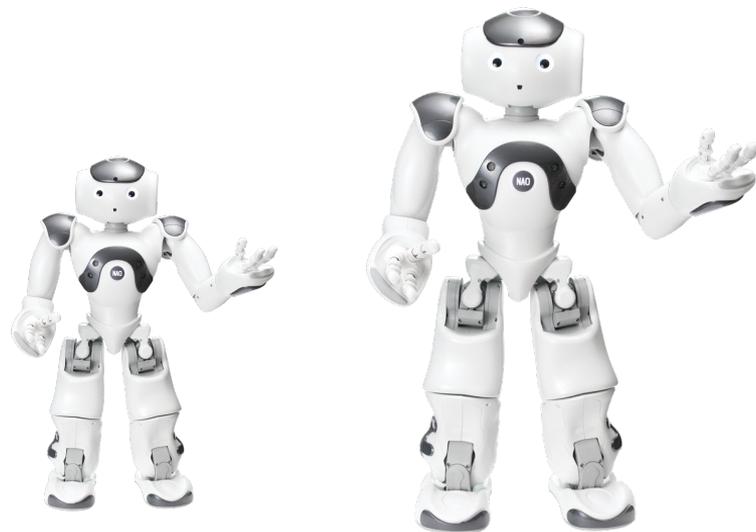
Important model, yet not feasible in practical applications.

Action Robustness in Robotics

Abrupt disturbances



Model uncertainty



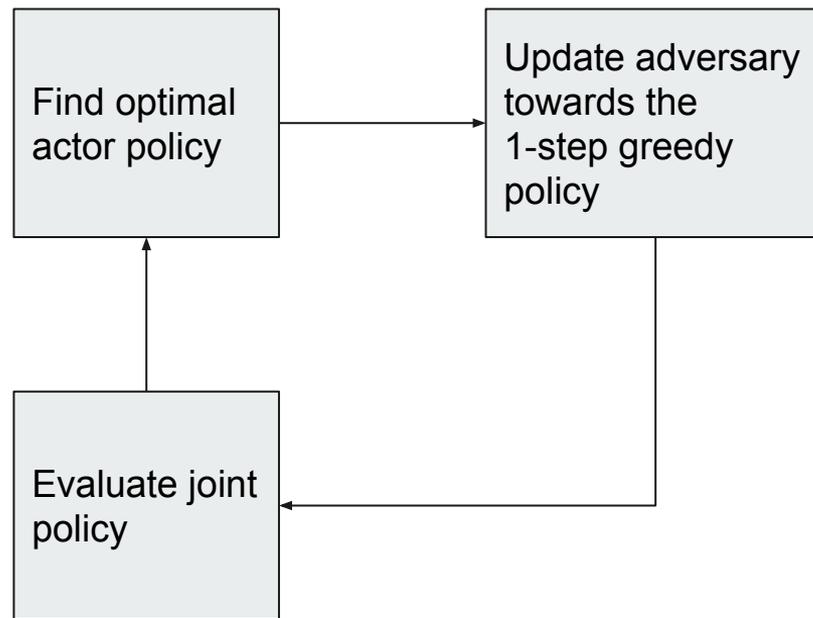


Action Robust MDPs

$$\pi_{\alpha}^{\text{mix}}(\pi, \pi') = \begin{cases} \pi & \text{w.p. } 1 - \alpha \\ \pi' & \text{otherwise} \end{cases}$$

AR-MDPs are a special case of RMDPs, which consider uncertainty in the performed action.

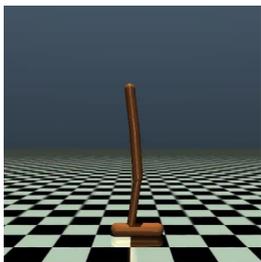
Algorithm



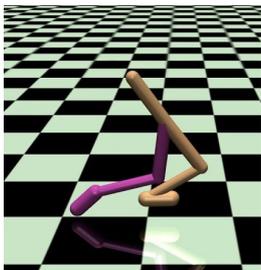
Theorem 1. *This procedure converges to the Nash equilibrium.*



Results

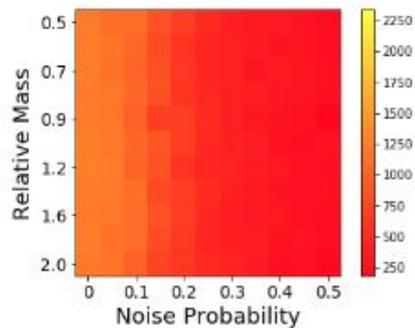


Hopper

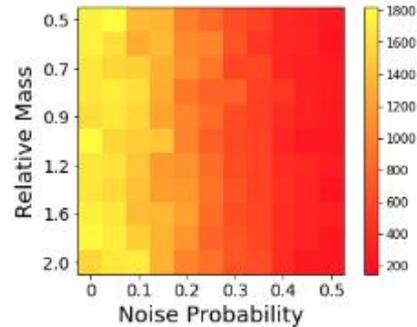
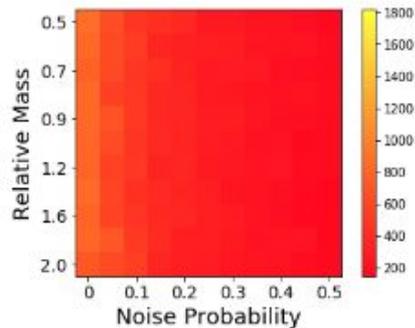
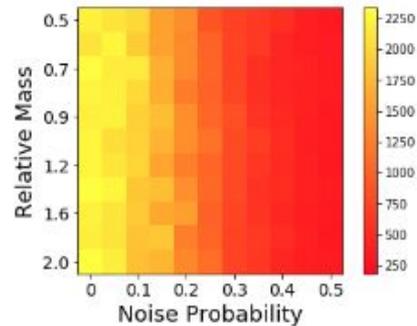


Walker2d

Baseline



Ours($\alpha=1$)



Conclusions

- Robustness enables coping with **uncertainty** and **transfer** to unseen domains
- A **gradient based** approach for robust reinforcement learning with convergence guarantees
- **Does not require** explicit definition of the **uncertainty set**
- Application to **Deep RL**

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