A Multiplicative Value Function for Safe and Efficient Reinforcement Learning

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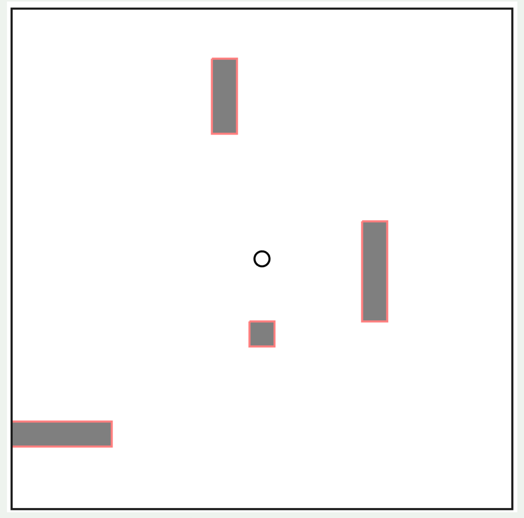
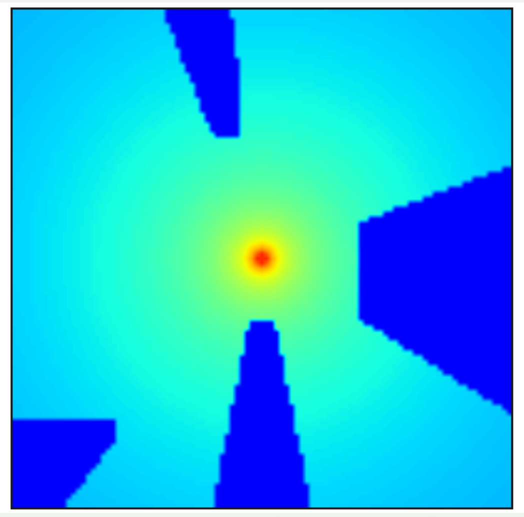
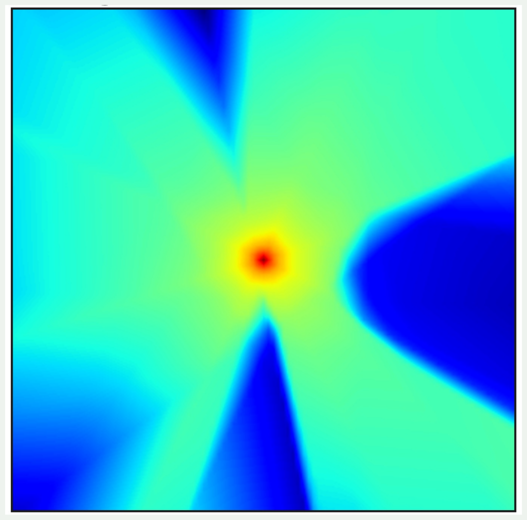
Motivation



Environment with Constraints

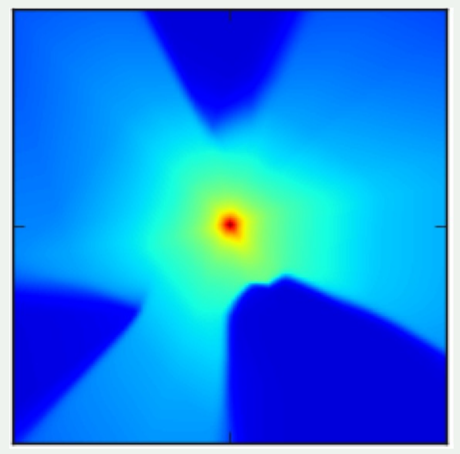


Ground-Truth Value



Regular Value Function

- **Sharp discontinuities are hard to learn.**
- **Poor training stability and sample efficiency.**



Multiplicative Value Function

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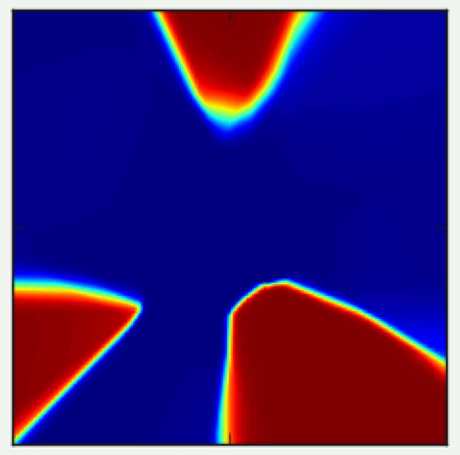
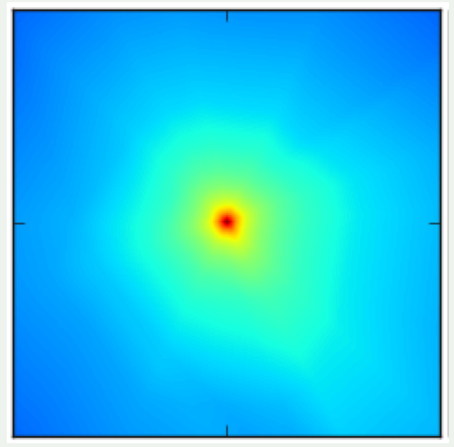


Probabilistic Safety Critic

$\otimes$



Constraint-Free Reward Critic

Method

Multiplicative Value/Q Function:

$$V^{\pi}_{\text{mult}}(s) = (\bar{V}^{\pi}(s) - \bar{v}_{min}) \cdot (1 - \Phi^{\pi}(s)) + \bar{v}_{min}$$

$$Q^{\pi}_{\text{mult}}(s,a) = (\bar{Q}^{\pi}(s,a) - \bar{q}_{min}) \cdot (1 - \Psi^{\pi}(s,a)) + \bar{q}_{min},$$

$$\bar{v}_{min} \coloneqq \min_{s} \bar{V}^{\pi}(s), \bar{q}_{min} \coloneqq \min_{s,a} \bar{Q}^{\pi}(s,a)$$

Multiplicative Advantage:

(V1) Bootstrap Q:

$$A^{\pi}_{\text{mult}}(s_t,a_t) = [\bar{r}_t + \gamma V^{\pi}_{\text{mult}}(s_{t+1})] - V^{\pi}_{\text{mult}}(s_t)$$

(V2) W/O bootstrap: $A^{\pi}_{\text{mult}}(s_t,a_t) = Q^{\pi}_{\text{mult}}(s_t,a_t) - V^{\pi}_{\text{mult}}(s_t)$

(V3) Bootstrap the safety critic inside $Q^{\pi}_{\text{mult}}(s_t,a_t)$:

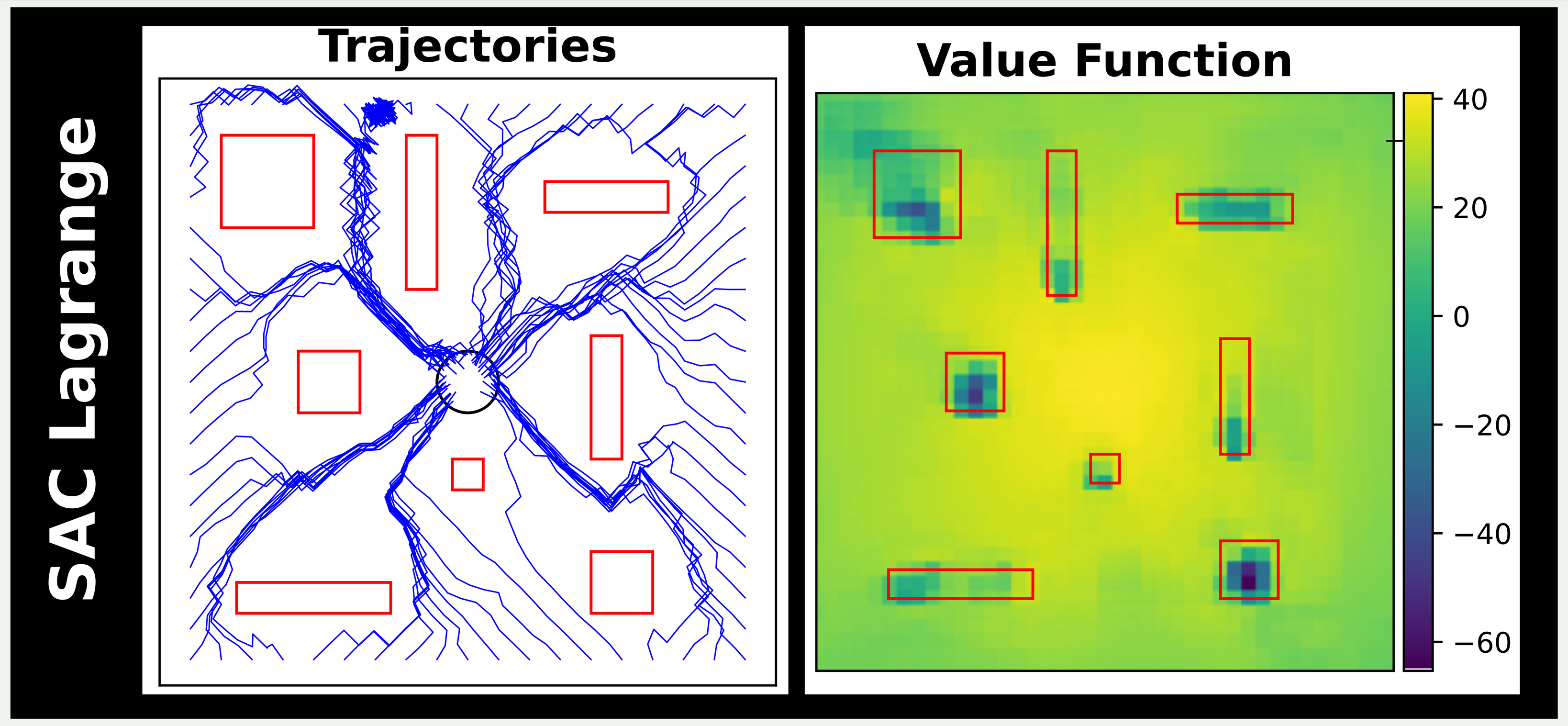
$$(\bar{Q}^{\pi}(s_t,a_t) - \bar{q}_{min}) \cdot (1 - (r_{c,t} + \gamma_c \Phi^{\pi}(s_{t+1})))) + \bar{q}_{min}$$

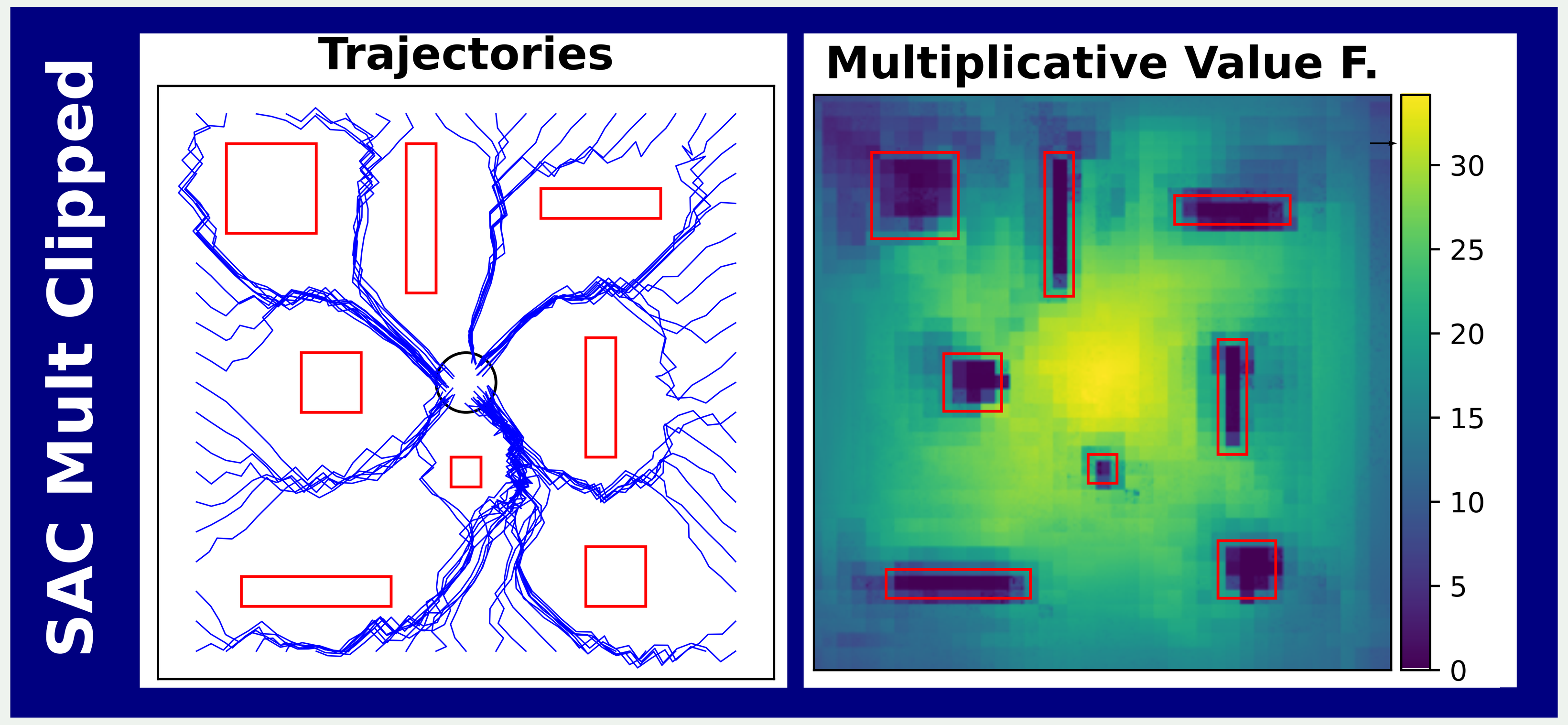
Apply to SAC and PPO

SAC: $\max_{\theta} \mathbb{E}_{a_\theta \sim \pi_\theta} \left[Q^{\pi_\theta}_{\text{mult}}(s,a_\theta) - \alpha \log \pi_\theta(s_\theta|x) \right]$

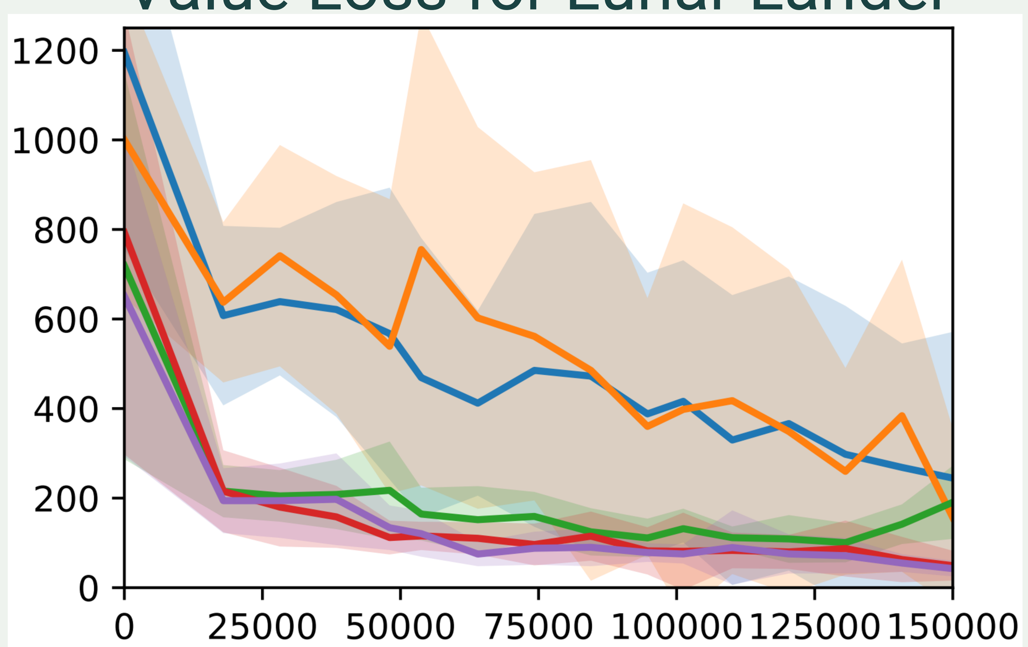
PPO:
$$\max_{\theta} \mathbb{E}_{a \sim \pi_\theta} \left[\min \left\{ \frac{\pi_\theta(a|s)}{\pi_{\theta_k}(a|s)} A^{\pi_{\theta_k}}_{\text{mult}}(s,a), g\left(\epsilon, A^{\pi_{\theta_k}}_{\text{mult}}(s,a)\right) \right\} \right]$$

Results





Value Loss for Lunar Lander



Improved

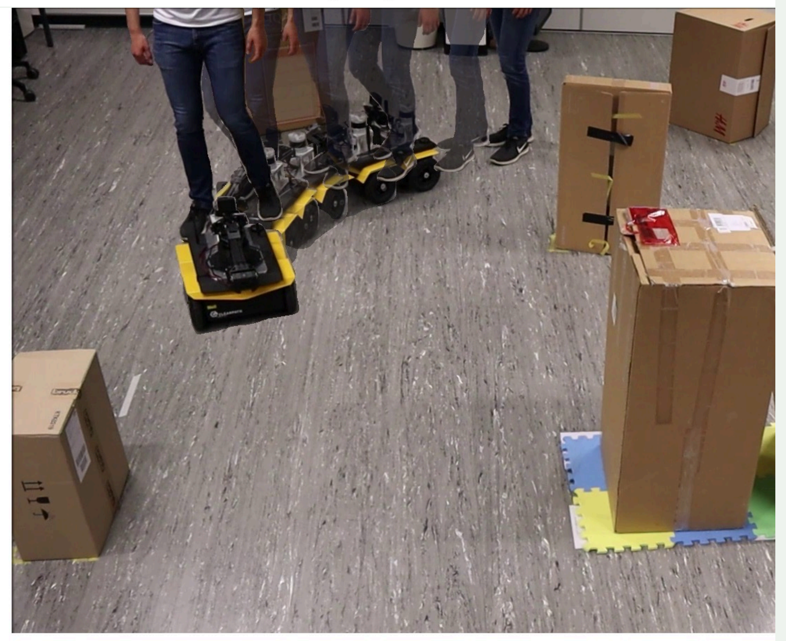
- **Training stability**
- **Sample efficiency**
- **Value matching to the obstacles**

Real-World Experiments

(a)

(b1)

(b2)



(c)

- **Differential drive robot with 1D-Lidar.**
- **Training in Gazebo Simulation.**
- **Zero-Shot Sim-to-Real.**
- **Safe Interaction with Dynamic Objects and Human.**

Summary

- **Multiplicative Value Function**
  - Safety Critic: Binary decision problem.
  - Reward Critic: Constraint-free RL.
- **Integration into SAC and PPO:**
  - Increased sample efficiency and learning stability.
- **Future works:** Theoretical justification.
- **Code:** github.com/nikeke19/Safe-Mult-RL
- **Homepage with Videos:** zhejz.github.io/saferl