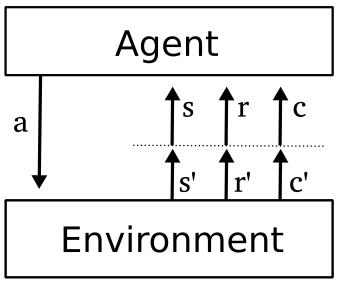
## AlwaysSafe

Reinforcement Learning without Safety **Constraint Violations during Training** Thiago D. Simão Nils Jansen Matthijs Spaan

- Constrained MDPs models safety requirements explicitly.
- How to learn without violating the safety constraints?

### **Constrained RL**



$$\mathcal{M}=\langle \mathbb{S},\mathbb{A},\mathsf{P},\mathsf{R},\mu,\mathsf{C},\hat{c}
angle$$

$$\max_{\pi} V_{R}^{\pi}(\mu) = \mathbb{E}_{\pi} \left[ \sum_{t=1}^{H} r_{t} \mid \mu \right]$$
  
s. t.  $V_{C}^{\pi}(\mu) = \mathbb{E}_{\pi} \left[ \sum_{t=1}^{H} c_{t} \mid \mu \right] \leq \hat{c}$ 

Salely constraint

### **Cost-model-irrelevant** Abstraction

$$\begin{split} \bar{\mathcal{M}}_{\phi} &= \langle \bar{\mathbb{S}}, \mathbb{A}, \bar{P}, \bar{R}, \bar{\mu}, \bar{C}, \hat{c} \rangle \\ \hline & \uparrow \\ \phi : \mathbb{S} \to \bar{\mathbb{S}} \\ \hline & \mathcal{M} &= \langle \mathbb{S}, \mathbb{A}, P, R, \mu, C, \hat{c} \rangle \end{split}$$

 $\phi$  preserves the expected cost:

$$V^{\pi, \mathcal{ar{M}}_{\phi}}_{ar{\mathcal{C}}}(ar{\mu}) = V^{\pi, \mathcal{M}}_{\mathcal{C}}(\mu)$$

- The abstract policy  $\pi_A$  is safe but might be suboptimal.
- The ground policy  $\pi_G$  can reach optimality but has no safety guarantees.



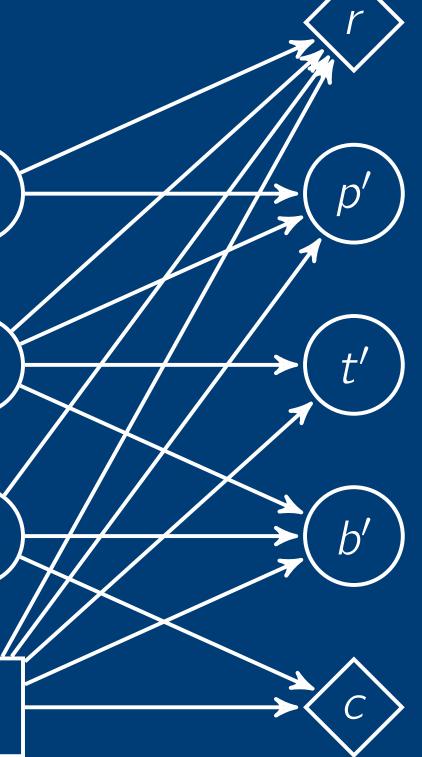




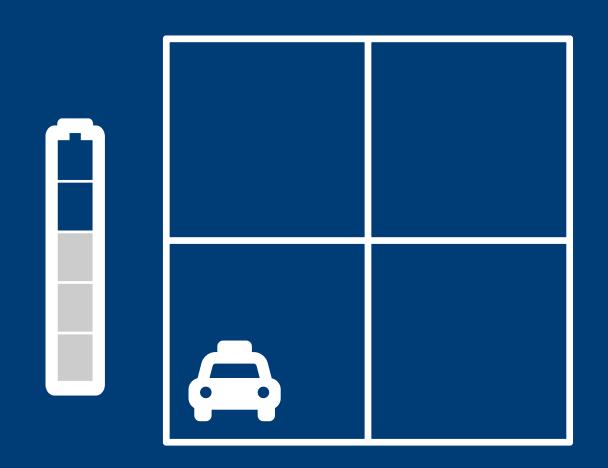
# Not everything is relevant for safety

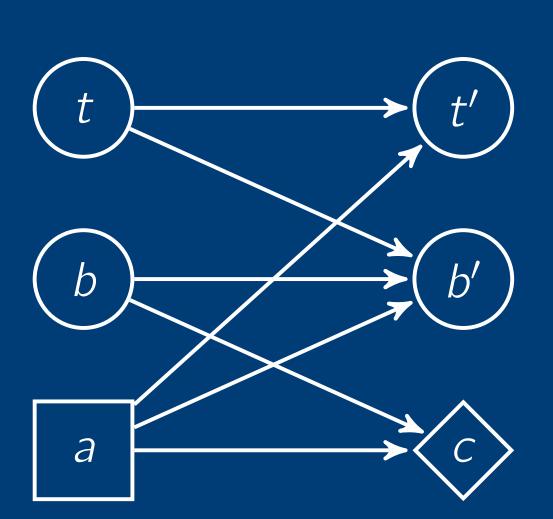
To prevent a taxi from running out of fuel it is not necessary to know the position of the passenger.





Factored MDP with cost function related to safety



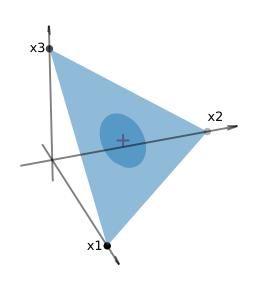


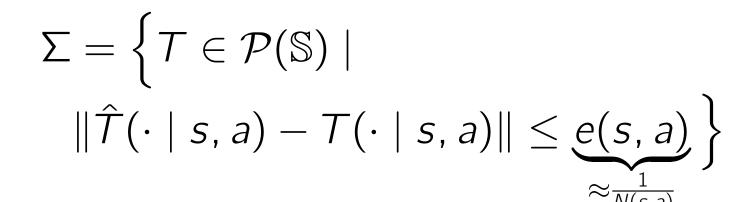
Abstraction of the safety dynamics

Find more at: https://tdsimao.github.io/publications/Simao2021alwayssafe/



#### **Uncertainty set**

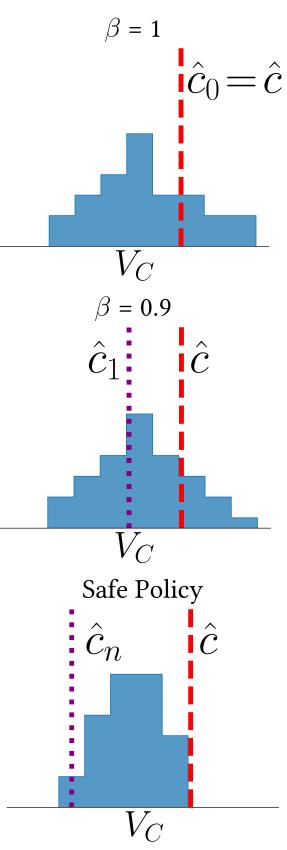




 $\Sigma$  contains the true transition function with high probability.

### **Conservative policy**

Tight safety constraint until ground policy is safe in all probable CMDPs ( $\Sigma$ ).



### Results

