Safe Reinforcement Learning Via Shielding

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Prelimaries

Motivation

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However, traditional RL approaches do not inherently prioritize safety during the learning or execution phases. This lack of safety assurance can be particularly concerning in critical applications where incorrect actions could lead to harmful or catastrophic outcomes.

Therefore, there is a growing need to develop methods that not only optimize for reward but also ensure adherence to safety specifications throughout the learning process.

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The system works in a interaction between an agent and an environment.

RL: Continued

Beginning at s_t, the agent picks an action a_t at time t, it goes to a state s_{t+1} based on the distribution described by $\mathcal{P}$, and it gets a reward r_{t+1} based on $\mathcal{R}$

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The objective of the agent is to find a policy π, a function from S to $\mathcal{A}$ which maximizes the Expected Value of $\sum_{t=0}^{\text{inf}} \gamma^t \cdot r_t$

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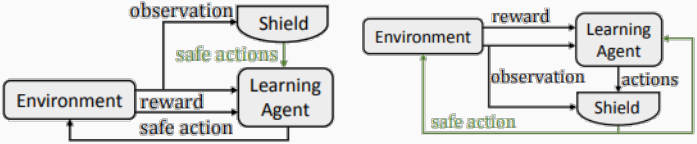
Working

In Teacher-Guided Reinforcement Learning (RL), a human or external entity, known as the teacher, intervenes to provide guidance and advice to the learning agent, particularly in scenarios where safety is paramount. The teacher observes the agent's actions and can suggest safe actions or steer the agent away from potentially harmful decisions. This intervention aims to prevent undesirable outcomes and ensure the efficacy of the learning process.

One common application of Teacher-Guided RL is in Q-learning, where the teacher advises the agent on safe actions when necessary. Unlike traditional RL, where the agent learns solely from trial and error, Teacher-Guided RL incorporates external knowledge to enhance safety and guide the learning process toward more desirable outcomes.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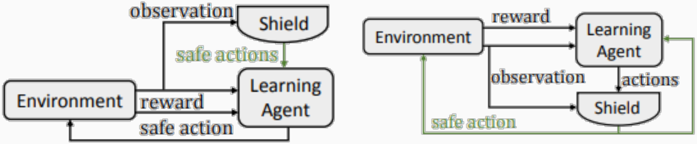
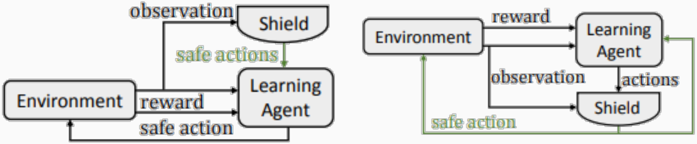


The image above describes the framework for Shielding. The two types of Shielding are Preemptive and Post-Posed.



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Their separate working and properties are described later. The general framework tries to make the agent avoid actions that shield considers as unsafe, keeping an upper bound of changes in mind.

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If the chosen action is deemed unsafe based on the system's specifications and environment dynamics, the shield overwrites it with a safe alternative. This proactive approach minimizes interference with the agent's learning while prioritizing the preservation of safe system behavior.

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This set is derived by considering all available actions and filtering out those that would violate the safety specification ϕ_s. The agent then receives this filtered list from the shield and selects an action $a_t \in \{a_1^t, \ldots, a_k^t\}$.

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Subsequently, the environment executes the chosen action a_t, transitions to the next state s_{t+1}, and provides the reward r_{t+1}. Essentially, the role of the shield is to dynamically adjust the available actions for the agent at each time step to ensure that only safe actions are considered.

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For every state $s \in S_0$, a new subset of available actions $\mathcal{A}_0 \subseteq \mathcal{A}$ is created by applying the shield to $\mathcal{A}$, eliminating all unsafe actions. Transition function P_0 from each state $s \in S_0$ contains only transition distributions from P for actions within $\mathcal{A}_0$.

The Post-Posed shield monitors the agent's actions and replaces them with safe alternatives when necessary to avoid violating ϕ_s. At each step t, the agent selects an action a_1^t. If a_1^t is unsafe with respect to ϕ_s, the shield substitutes it with a safe action a_1^t instead.

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The environment then executes a_1^t, transitions to s_{t+1}, and provides r_{t+1}. The agent receives a_1^t and r_{t+1}, updating its policy accordingly. There are two approaches to handling the reward for a_1^t when it's replaced

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Post-Posed Reward Updates

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- Assign the reward r_{t+1} to a_1^t. The agent updates the unsafe action with the reward, potentially including unsafe actions in an optimal policy. Since unsafe actions are always replaced with safe ones, this doesn't pose an issue, but the shield remains necessary during learning and execution.

Post-Posed: Properties

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Remarkably, the learning agent doesn't even require awareness of being shielded.

Specifying for RL as LTL

Water Storage

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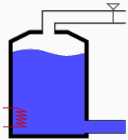

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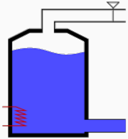

Water flows out at 0-1 liters/sec, and in at 1-2 liters/sec when the valve's open (closed otherwise). The tank holds 100 liters max, and valve changes need a 3-second minimum to preserve it. Overflow and running dry must be prevented.

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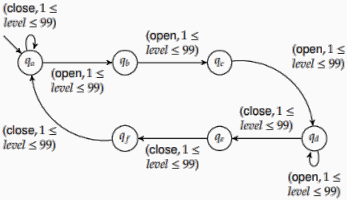

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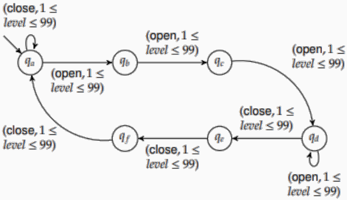
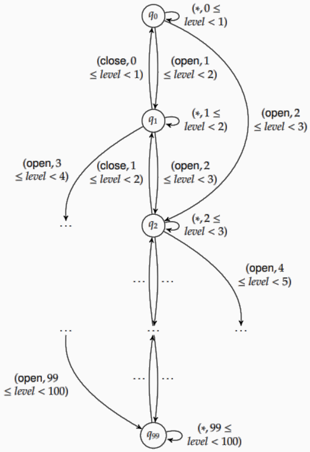
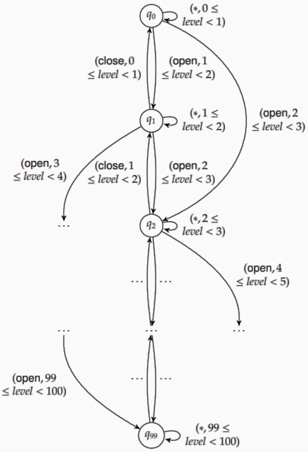


The above Temporal Path shows the available transitions in our model.

Synthesis

Further Specifications





Like how the previous abstraction, only cared about the specification about the Water Heater being in the same state for at-least 3 seconds, this takes care of the level of water not overflowing or drying out.

Since the previous two specifications do not use a fail state, we take the product of the pairwise elements from both the graphs, describe the transition and add a fail state.

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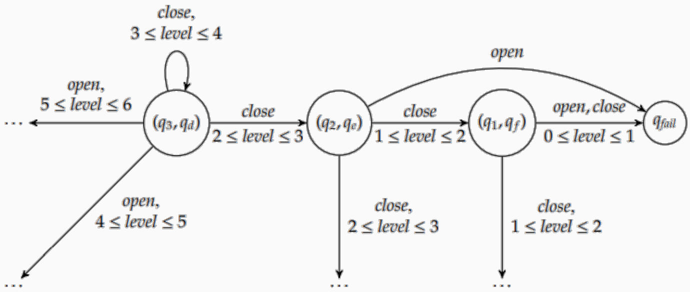

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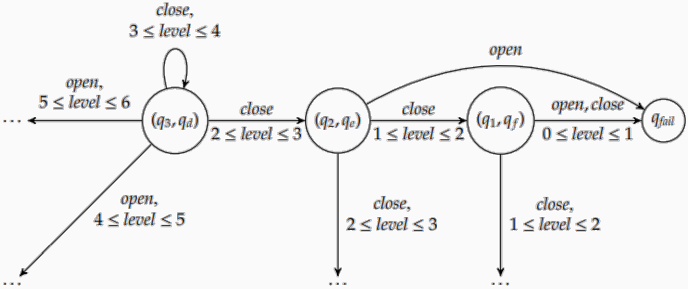

Using this, we can treat this as a Safety Game and check whether our current action leads to an unsafe state.

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If all the actions aren't unsafe, this provides a correct-by-construction method of keeping RL safe during learning and deployment.

Results

Water Tank

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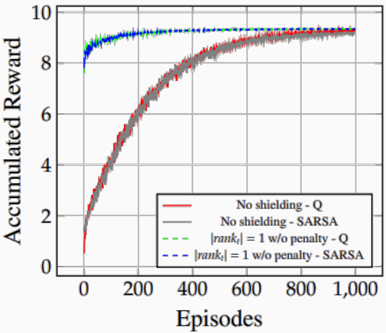

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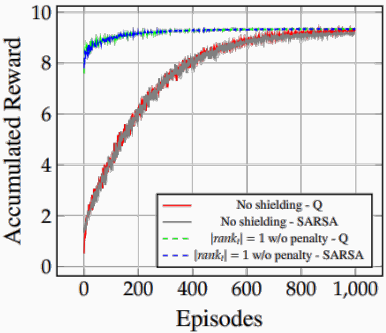
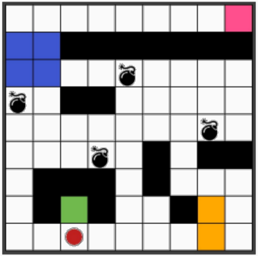
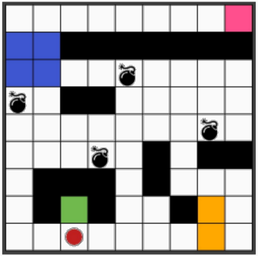


The above graph shows cumulative reward based on number of episodes. It shows how shielding fastens up the process while remaining safe.

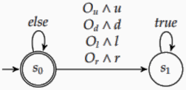
Grid Game

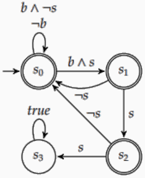


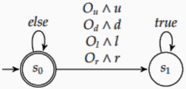


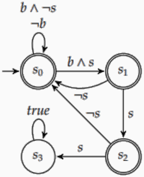
In the above game, the red-dot player has to avoid the walls and cant stay on the bomb for more than 2 consecutive steps while covering the colored squares in a particular order.

Grid Game: Continued









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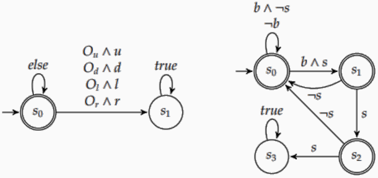

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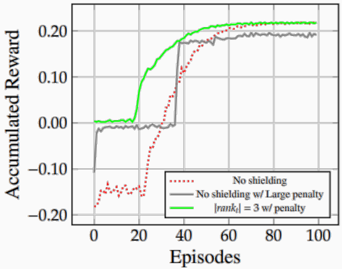

Conclusions

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In conclusion, this method introduces a novel approach to reinforcement learning by integrating safety constraints expressed as temporal logic specifications. By shielding the learning algorithm from violating these specifications, we ensure safer decision-making while minimizing the need for intricate understanding of the underlying learning process.

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Our experiments across various reinforcement learning scenarios demonstrate the effectiveness of shielded agents, consistently performing as well as, if not better than, unshielded counterparts. While constructing an abstraction for safety enforcement requires effort, our results underscore its significance in ensuring not only safe learning but also potentially enhancing learning performance.

Future Work

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- Explores the integration of a probabilistic shield. This would enable decision-making to adhere to safety constraints with high probability, enhancing the robustness of our learning system.
- Investigating this further could result in a boost up in the number of episodes required to reach convergence.

Thank You!