Safe Reinforcement Learning via Shielding

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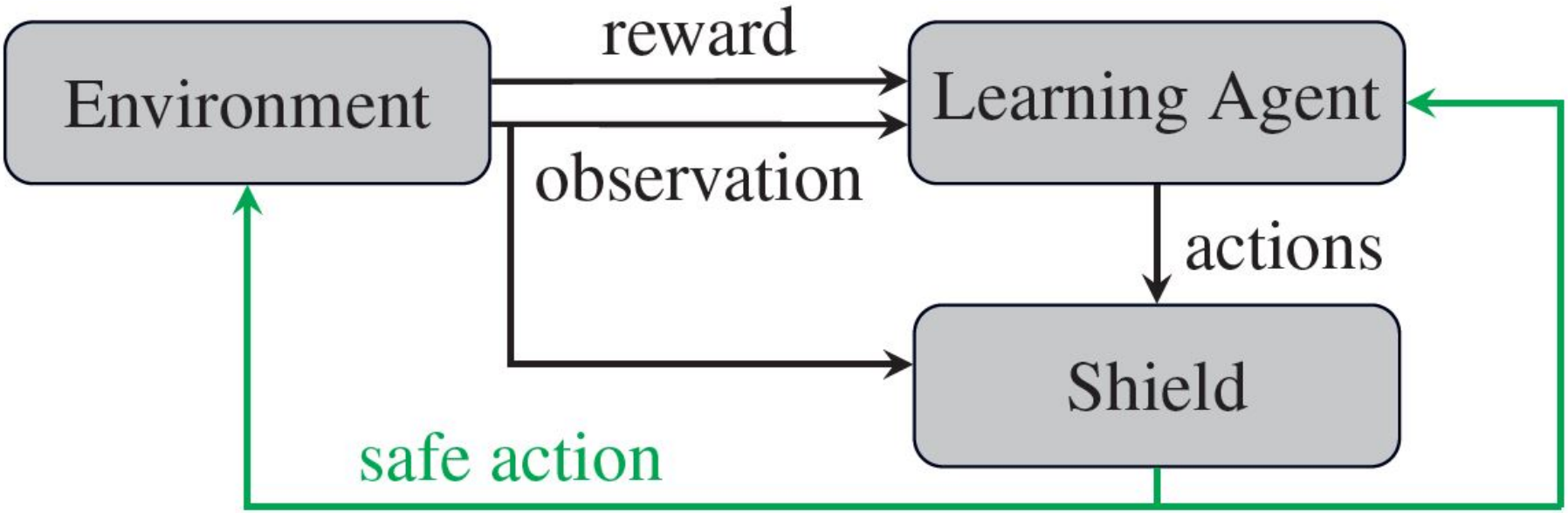
Motivation

- Increasing use of learning-based controllers in physical systems in the proximity of humans strengthens the concern of whether these systems will operate safely
- Safety or more generally correctness during learning and execution of controllers has attracted significantly less attention than optimality and convergence
- How can we let a learning agent do whatever it is doing, and also monitor and interfere with its operation whenever absolutely needed in order to ensure safety?

What is "Safe" Reinforcement Learning?

- A framework that allows applying machine learning to control systems in a way that the correctness of the systems execution is guaranteed
- The shield monitors the actions selected by the learning agent and corrects them if and only if the chosen action is unsafe
- Real-life application
  - Autonomous Vehicles
- How do we define "Correctness"?

Shielded Reinforcement Learning



Reinforcement Learning

- **Agent and Environment**: the agent operates in an environment and obtains a *reward* after every performed action
- **Goal**: an agent must learn an optimal policy through trial-and-error via interactions with an unknown environment modeled by an MDP
- **Q-function**: gives a measure of how good action a is in state s

$$Q^{\pi}(s,a) \equiv r(s,a) + \gamma \sum_{t=1}^{T-1} \gamma^{t-1} r_t$$

where:

Q: Value of taking action a in state s

r: Reward obtained from taking action a in state s

t: The current time step γ: Discount Factor

T: The total number of steps per episode

- **Optimal Policy**: computed as

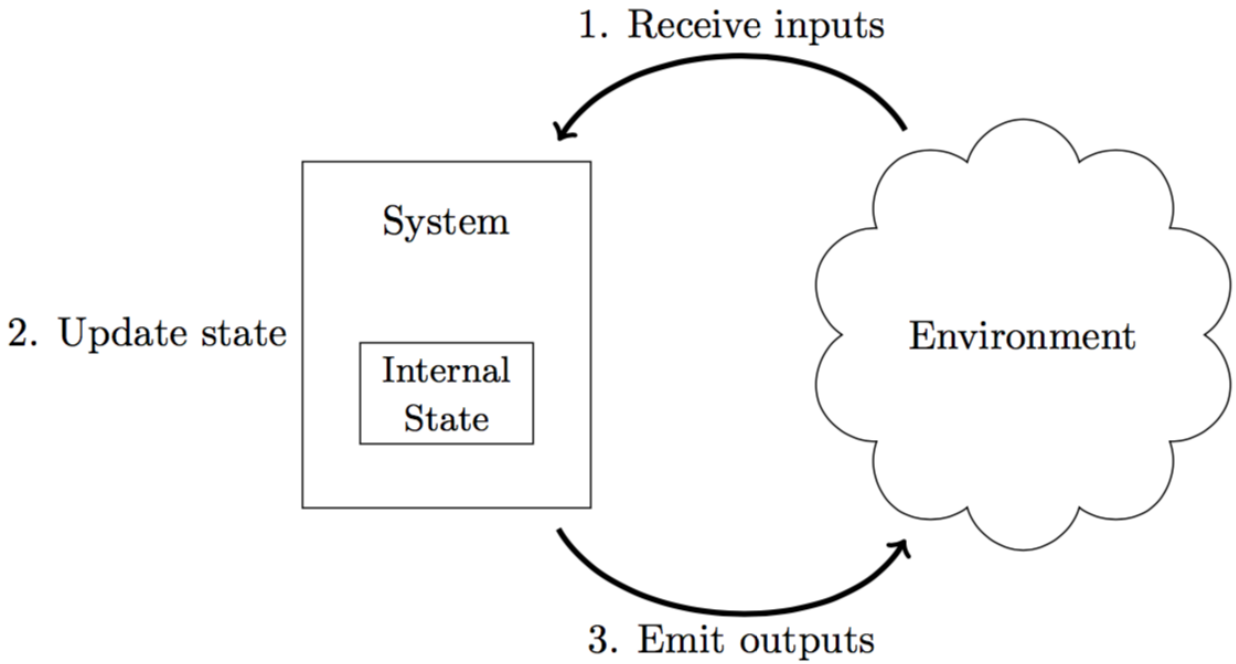
$$\pi^{\star}(s) = \arg\max_{a \in A} Q^{\star}(s,a)$$

Markov Decision Process

- Defined as $M =< S, s_I, A, P, R >$ where
  - S is a set of states
  - s_I is the initial state
  - A is a set of actions
  - P : transition function $P(s_{t+1}|s_t, a_t)$
  - $R : S \times A \times S \rightarrow \mathbb{R}$
- Solution to **MDP** called policy $\pi : S \rightarrow A$ that maximizes the cumulative discounted reward
- **RL** is the task of learning a possibly optimal policy, from an initial state s_I, on an MDP where only S and A are **known**, while P and R are **not known**.

Synthesis of Shields

Given: An LTL formula φ as specification with $Prop = \mathcal{I} \cup \mathcal{O}$.



Obtain: A model of a reactive system that **realizes** φ.

- For every sequence of inputs, the trace of the system satisfies φ.

Finite Reactive Systems

- Defined as $\mathcal{S} =< Q, q_0, \Sigma_I, \Sigma_O, \delta, \lambda >$ where
  - Q is a finite set of states
  - $q_I \in Q$ is the initial state
  - Σ_I : is the input alphabet
  - Σ_O : is the output alphabet
  - $\delta : Q \times \Sigma_I \rightarrow Q$ is the transition function
  - $\lambda : Q \times \Sigma_I \rightarrow \Sigma_O$ is the output function

Linear Temporal Logic - LTL

Allows expressing temporal patterns about a property (**over infinite traces**)

Syntax

$X\varphi$: φ is true in the next moment in time
$G\varphi$: φ is true forever
$F\varphi$: φ is true eventually
$\varphi \mathcal{U} \psi$: φ is true until ψ is true

Example

$$G(level > 0) \wedge G(level < 100) \wedge$$
$$\mathrm{G}((\mathrm{open} \wedge Xclose) \Rightarrow XXclose \wedge XXXclose) \wedge$$
$$\mathrm{G}((\mathrm{close} \wedge Xopen) \Rightarrow XXopen \wedge XXXopen)$$

LTL Introduces

Safety Specification φ^S: something bad should never happen
$G\neg(WaterLevel > 93)$

φ^S defines a set of allowed traces

The reactive system $\mathcal{S}$ realizes φ^S if for every sequence of inputs, the trace of the system realizes φ^S

LTL Safety Specification and **automata**

LTL safety specifications can be translated into a *safety word automaton* that represents it.

A DFA is a tuple $\varphi^s = \langle Q, q_0, \Sigma, \delta, F \rangle$

Q	is the finite set of states
$q_0 \in Q$	is the initial state
$\sum$	is the input alphabet
$F \subseteq Q$	is the set of safe states
$\delta : Q \times \Sigma \rightarrow S$	is the transition function

A *run* induced by the trace $\sigma = \{\sigma_0, \sigma_1, \sigma_2 ... \sigma_m\}$ is a sequence of states $q = q_0, q_1 ...$ such that $q_{i+1} = \delta(q_i, \sigma_i)\ \forall i \in N$.
A trace σ of a system S satisfies φ^s if the induced run visits only **safe** states, i.e., $\forall i \geq 0. q_i \in F$.

Example: Resource Arbiter

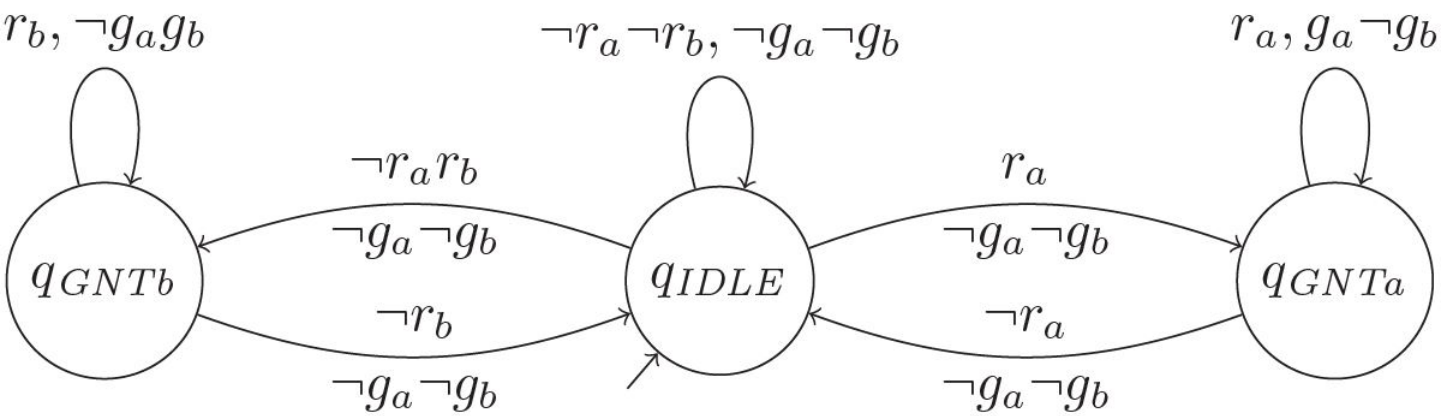
Synthesis of an arbiter:

- Two clients issue **requests** r_1, r_2 for access to shared resources.
- The arbiter produces **grants** g_1, g_2 granting access to the resources.

$$\varphi = G(\neg g_1 \vee \neg g_2) \wedge G(r_1 \Rightarrow F g_1) \wedge G(r_2 \Rightarrow F g_2)$$

The **specification** φ of the arbiter is the conjunction of:

1. **Mutual exclusion:** at no point in time should both g_1 and g_2 be true.
2. **Response:** every request r_i from client i (for $i \in \{1, 2\}$) should eventually be followed by grant g_i for client i.



Abstraction

- Planning ahead does not require the environment dynamics to be completely known in advance
- A (coarse finite-state) abstraction of the environment dynamics is needed to reason about when exactly a specification violation cannot be avoided
- Abstraction has to be conservative w.r.t. the behavior of the real MDP
- Abstraction may have finitely many states even if the MDP has infinitely many states

Abstraction

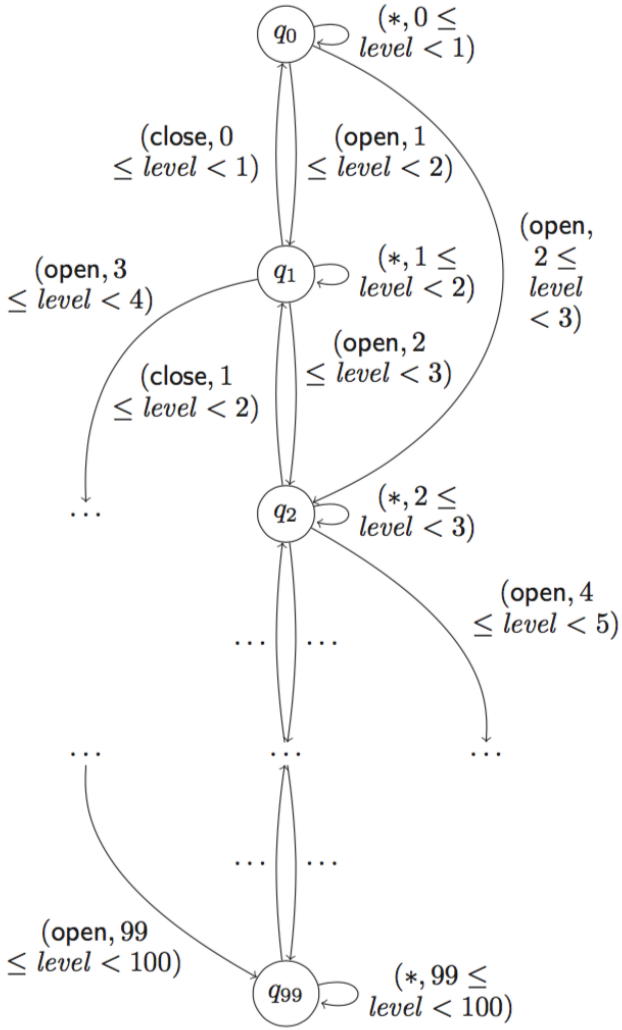
Given an MDP $M =< S, s_I, A, P, R >$ and an *MDP Observer Function* $f : S \to L$

An Abstraction is a tuple $\varphi^{\mathcal{M}} = \langle Q_{\mathcal{M}}, q_{0,\mathcal{M}}, \Sigma, \delta_{\mathcal{M}}, F_{\mathcal{M}} \rangle$

$Q_{\mathcal{M}}$	is the finite set of states
$q_{0,\mathcal{M}} \in Q$	is the initial state
$\Sigma = A \times L$	is the input alphabet
$F \subseteq Q$	is the set of safe states

The transition function, $\delta_{\mathcal{M}}$, specifies the next state as, for every trace $s_0, s_1 ... \in S$ with the corresponding action sequence $a_0, a_1 ... \in A$ of the MDP, for every automaton run $q = q_0, q_1 ... Q$ of $\varphi^{\mathcal{M}}$: $q_{i+1} = \delta_{\mathcal{M}}(q_i, l_i, a_i))$ for $l_i = L(s_i)\ \forall \in \mathbb{N}$

Example


q_0
$(*, 0 \leq level < 1)$
$(\text{close}, 0 \leq level < 1)$
$(\text{open}, 1 \leq level < 2)$
$(\text{open}, 2 \leq level < 3)$
q_1
$(*, 1 \leq level < 2)$
$(\text{open}, 3 \leq level < 4)$
$(\text{open}, 2 \leq level < 3)$
$(\text{close}, 1 \leq level < 2)$
q_2
$(*, 2 \leq level < 3)$
$(\text{open}, 4 \leq level < 5)$
$(\text{open}, 99 \leq level < 100)$
q_{99}
$(*, 99 \leq level < 100)$

Synthesis through Safety Games

- Translate φ^s and $\varphi^{\mathcal{M}}$ to a safety game $\mathsf{G} = (\mathsf{G}, g_0, \Sigma_I, \Sigma_O, \delta, F^g)$ between two players.
- Compute the winning region $\mathsf{W} \subseteq F^g$ of G
- Translate G and W to a reactive system $\mathsf{S} = (Q_S, q_{0,\mathcal{S}}, \Sigma_{I,S}, \Sigma_{O,S}, \delta_S, \lambda_S)$, that constitutes the shield.

Interaction of Shield & Agent

The shield monitors the actions of the agent, and substitutes the selected actions by safe actions whenever this is necessary to prevent the violation of φ^S

Shield

- In each step t, the agent selects an action a_t^1
- The shield forwards a_t to the environment, i.e., $a_t = a_t^1$.
  Only if a_t^1 is unsafe w.r.t. φ^S, the shield selects a different action $a_t \neq a_t^1$ instead.
- The environment executes a_t, moves to s_{t+1} and provides r_{t+1}.
- The agent receives a_t and r_{t+1}, and updates its policy for a_t using r_{t+1}

Rewards for **un**safe Actions

- Assign a punishment $r'_{t+1} < 0$ to a_t^1
  - The agent learns that selecting a_t^1 at state s_t is unsafe, without ever violating φ^S
  - No guarantee that unsafe actions are not part of the final policy
  - Shield has to remain active even after the learning phase
- Assign the reward r_{t+1} to a_t^1
  - Picking unsafe actions can likely be part of an optimal policy by the agent
  - Since an unsafe action is always mapped to a safe one, this does not pose a problem and the agent never has to learn to avoid it
  - Shield is (again) needed during the learning and execution phases

Experiments

Demonstration

Jupyter Notebook