Towards Best-Effort Autonomy

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Based on Joint work with Salar Moarref & Ufuk Topcu (CDC 2016)

Motivation

Highly autonomous systems...

- ... degrade in performance over time
- ... need to work correctly in off-nominal conditions
- ... need to adapt without the need of a human operator

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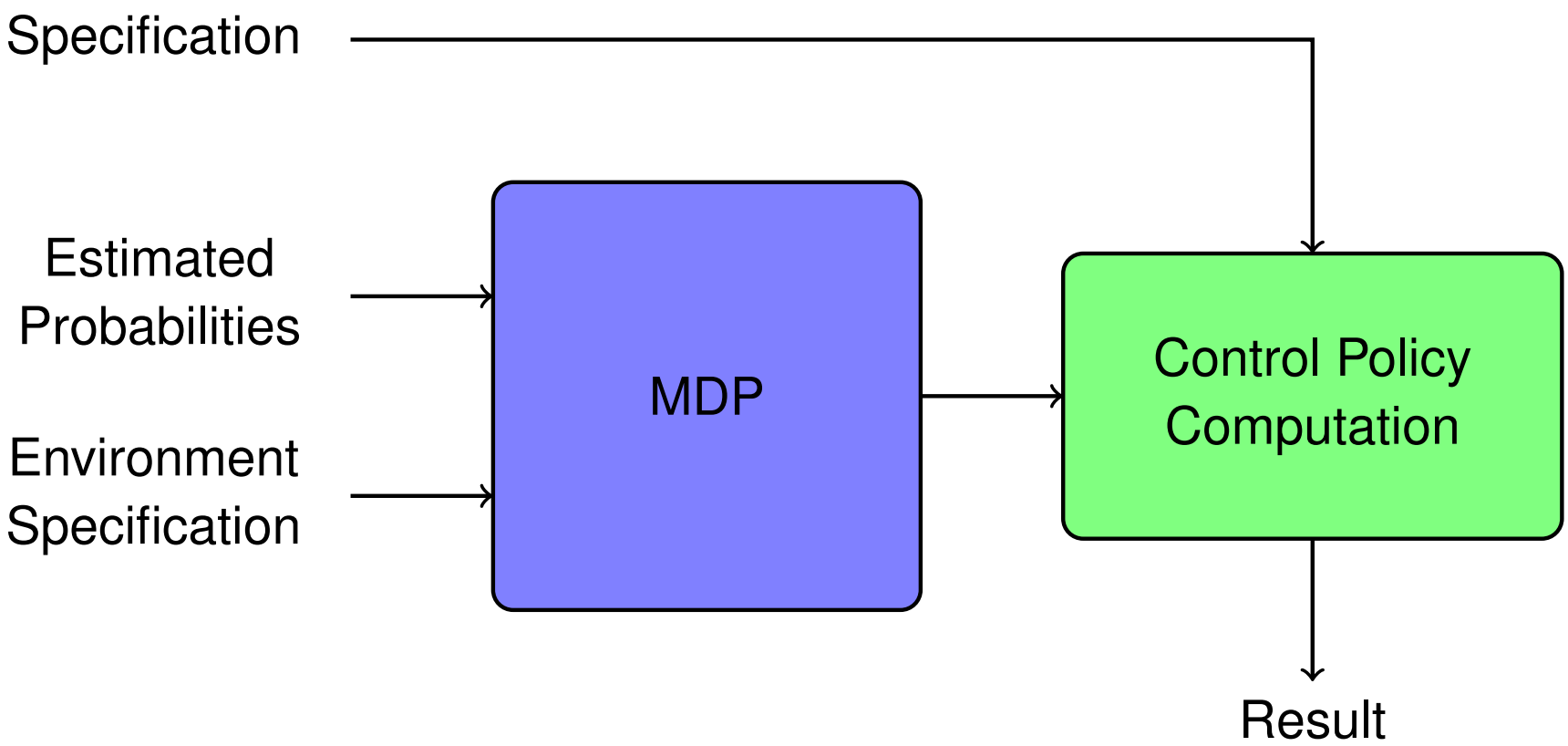
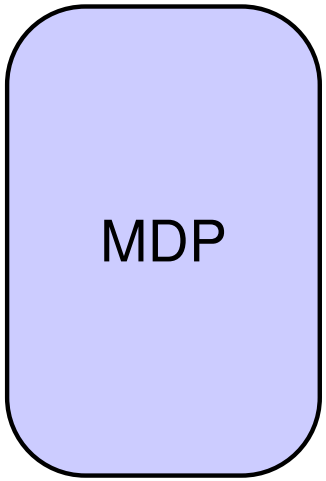
Problem:

- We do not always know in advance how they are degrading...
- ...so we should be able to *synthesize an adapted strategy* in the field

Connecting Theory and Practice....



ω-regular control of MDPs – basic setting



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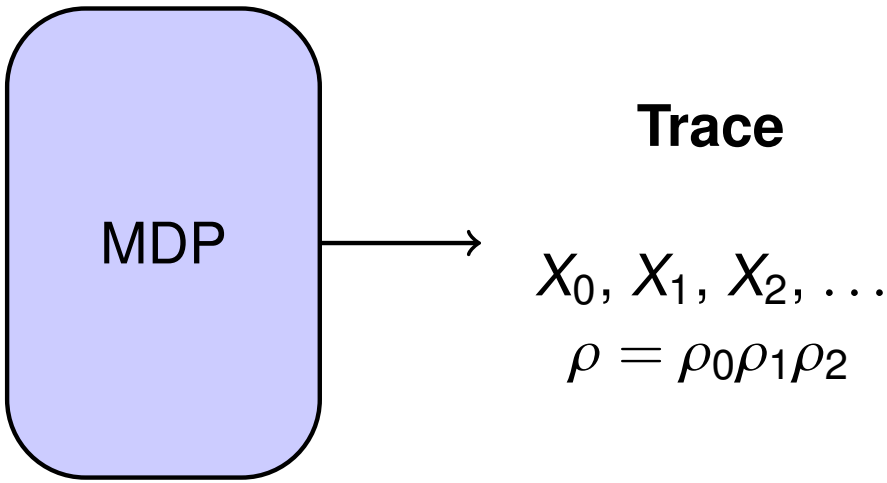

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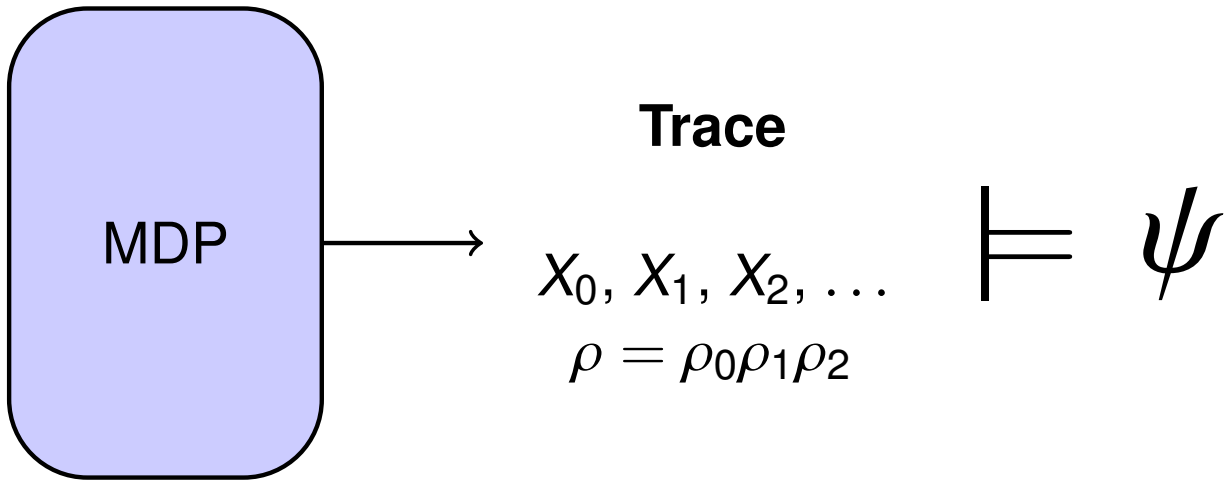

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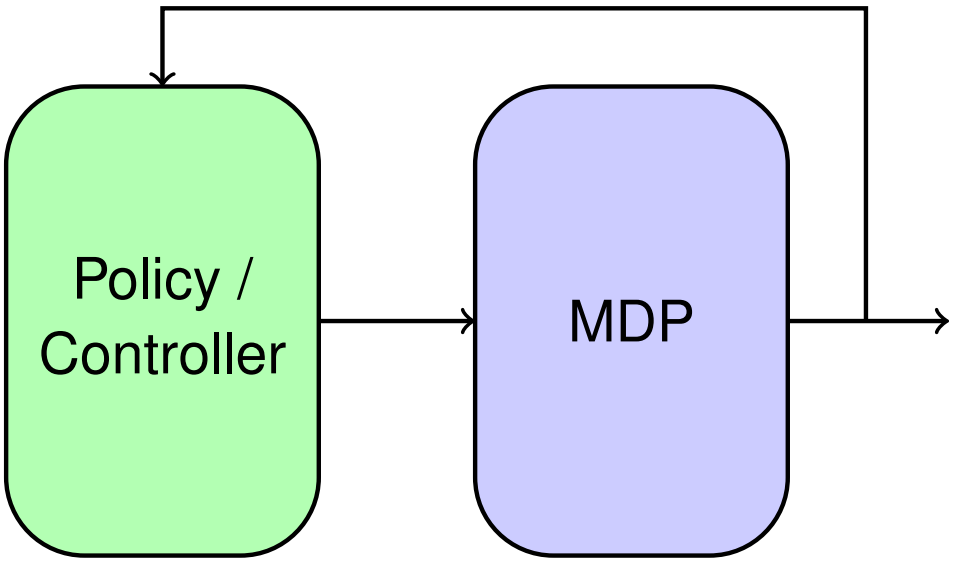

Trace

$X_0, X_1, X_2, \ldots$

$\rho = \rho_0\rho_1\rho_2$

$\models \psi$

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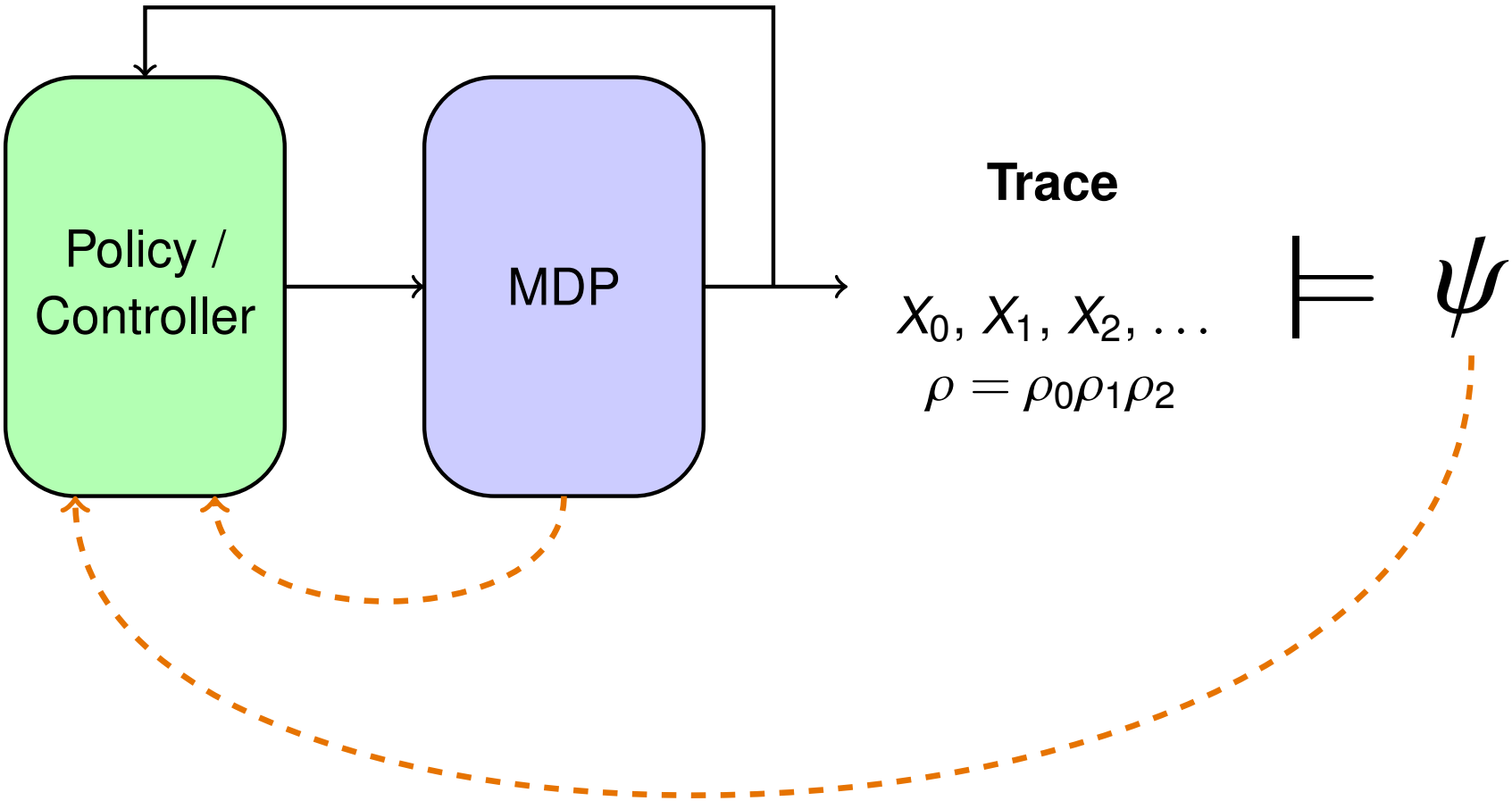
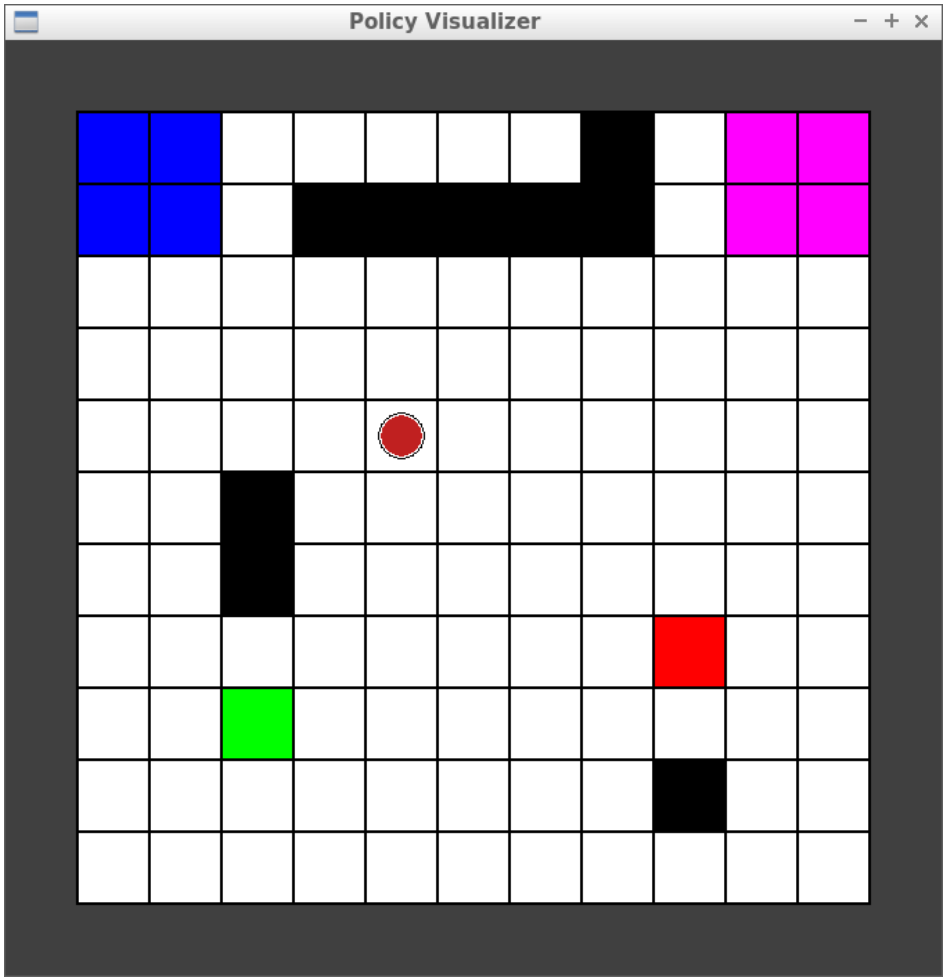
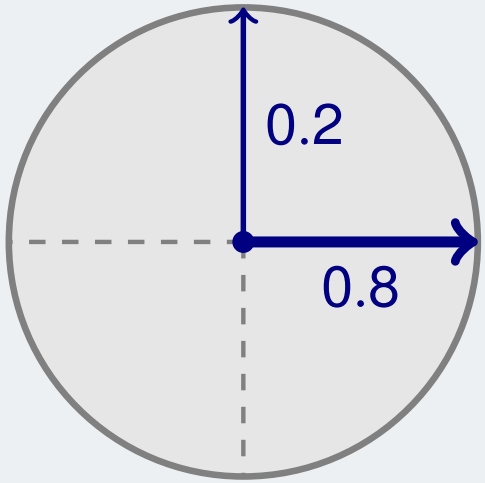


Simple example: patrolling



Motion primitives



Specification

$$\mathbf{GF}(\mathit{green}) \wedge \mathbf{GF}(\mathit{red}) \wedge \mathbf{GF}(\mathit{purple}) \wedge \mathbf{GF}(\mathit{blue})$$

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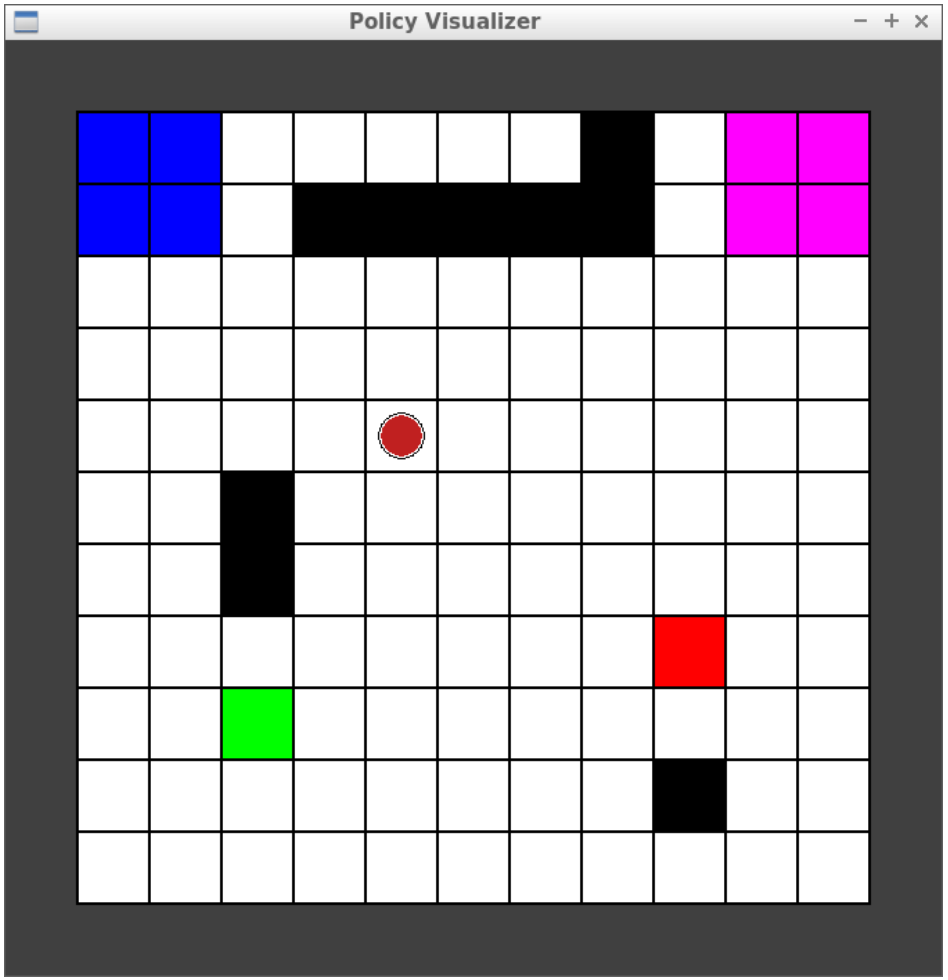

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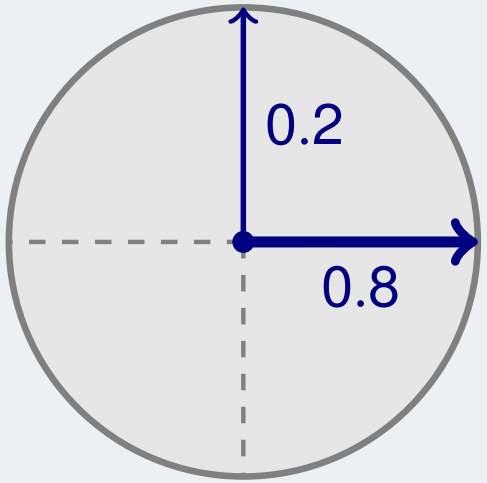

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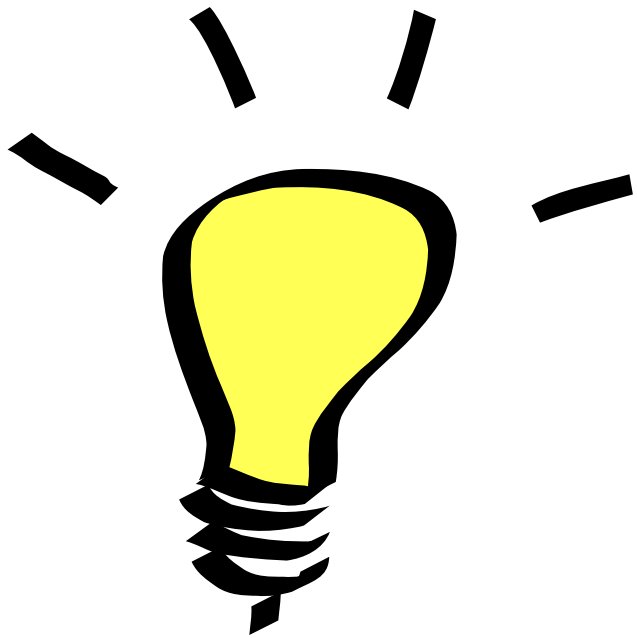
$$\mathcal{P}(\rho \models \psi) \geq (0.8)^4$$

Using ω-regular specifications

Ideas

- By assuming that **traces are infinitely long**, we can abstract from an unknown time until the system goes *out of service*.



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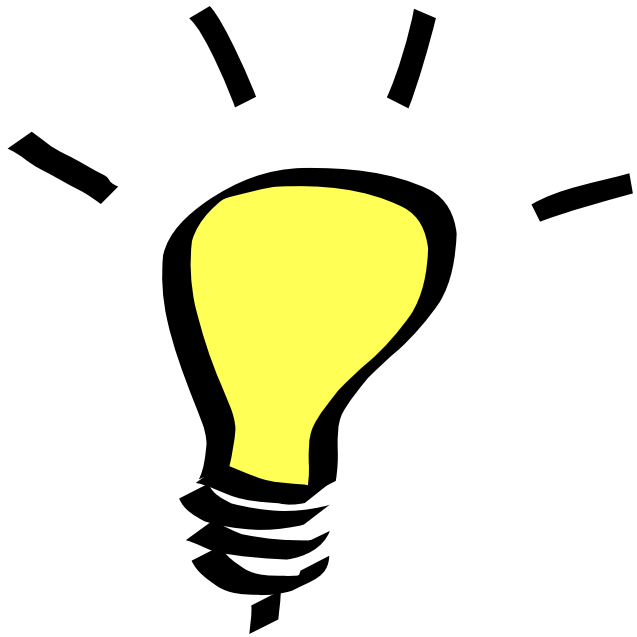

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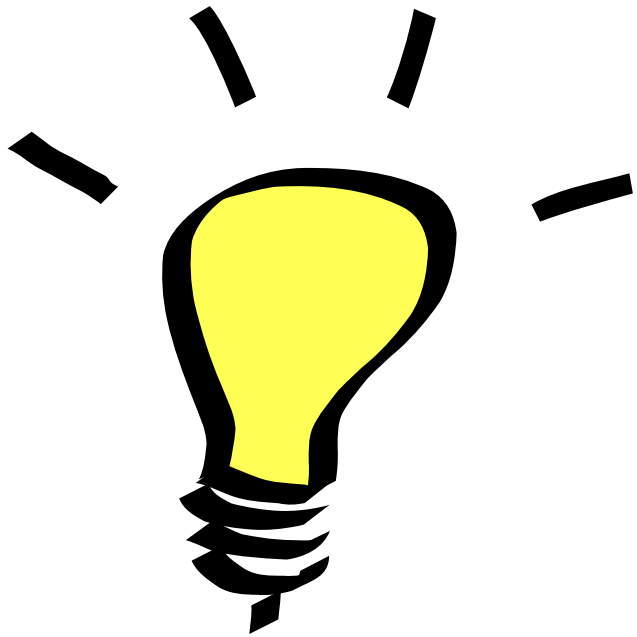
- ω-regular specifications allow us to specify relatively complex behaviors easily.



But do ω-regular specifications always make sense?

A thought experiment

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- At every second, $\mathcal{P}(\textit{robot breaks}) > 10^{-10}$.
- What is the maximum probability of satisfying the specification that some control policy can achieve? It's

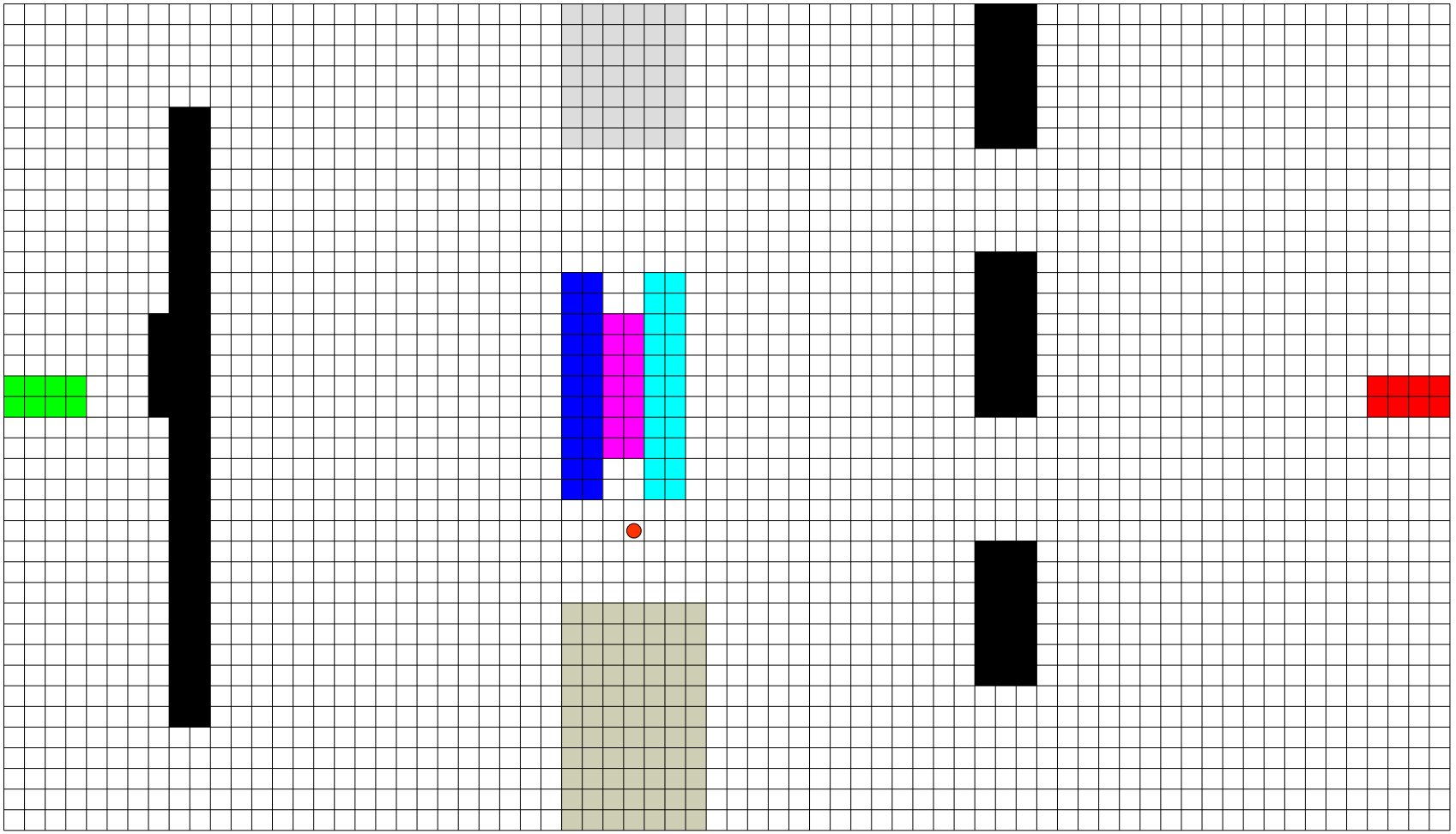
$$\mathbf{0}$$

as the robot will almost surely eventually break down.

Main question of the this paper

How can we compute policies
that work towards the satisfaction
of ω-regular specifications
even in the case of
inevitable non-satisfication?

Motivational example problem



Solving the problem by intuition

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We will all die, and it can happen any moment!

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Human behavior

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Example

Not doing risky driving

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Example

Not doing risky driving

So what we want is...

...a method to compute *risk-averse* policies that are at the same time *optimistic* that the catastrophic event does not happen.

Towards optimistic, but risk-averse policies (1)

Try 1

Compute policies that after reaching a *goal* maximize the probability of reaching the respective next goal.

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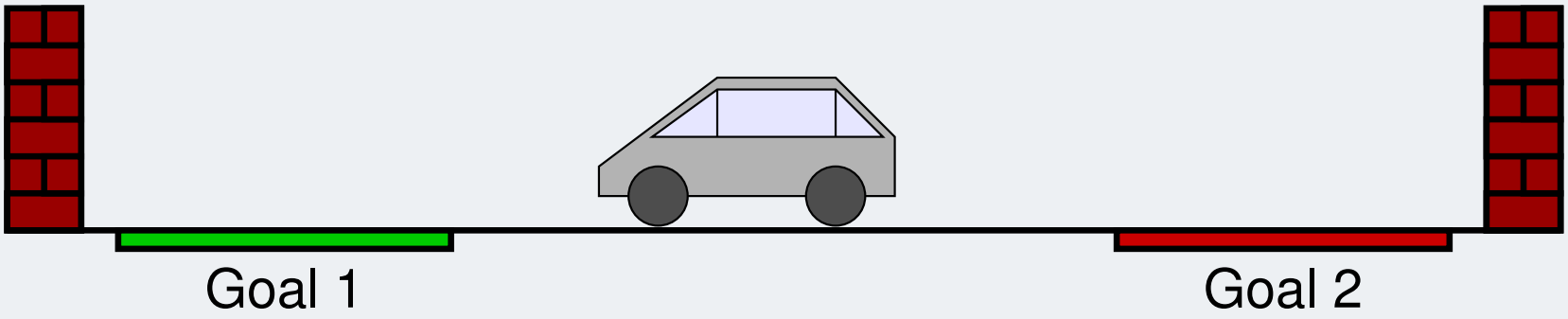

Specification: $\mathbf{GF}(goal_1) \wedge \mathbf{GF}(goal_2) \wedge \mathbf{G}(\neg crash)$

Prob. car breaks: 10^{-10} (every second)

Towards optimistic, but risk-averse policies (2)

Try 2 (similar to the work by Svorenova et al., 2013)

Compute policies that maximize some value p such that whenever a *goal* is reached, the probability of reaching the respective next goal is at least p.

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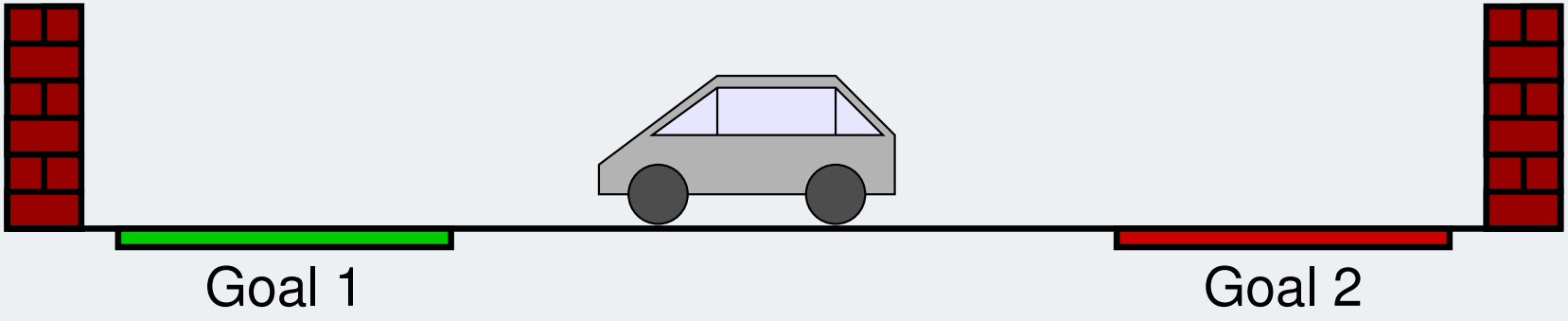
The same example as before



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Towards optimistic, but risk-averse policies (3)

But what about general ω-regular specifications?

Example:

$$(\mathbf{GF}(\mathit{red}) \wedge (\neg \mathbf{blue}\, \mathcal{U}\, \mathit{green})) \vee (\mathbf{FG}(\neg \mathit{blue}) \wedge \mathbf{GF}(\mathit{yellow}))$$

What are the goals here and how can we compute risk-averse policies?

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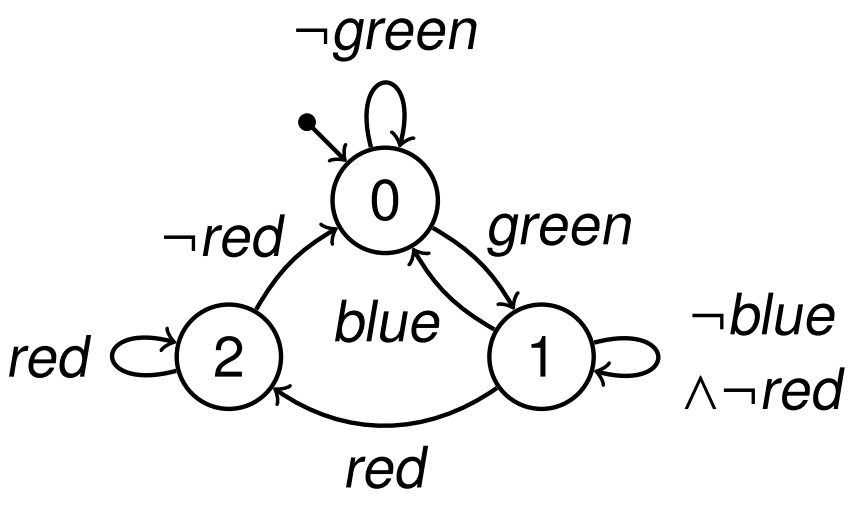
Idea

Let the policy **declare** the goals. Then we can compute a policy together with its declaration.

Declaring goals

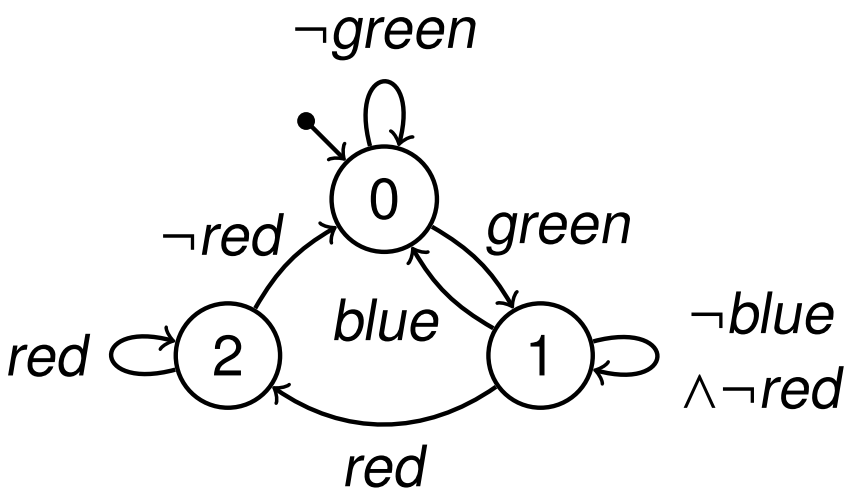
$$
\begin{aligned}
& (\mathbf{FG}(\mathit{red}) \\
\vee\ & \mathbf{F}(\mathit{blue} \wedge \mathbf{XG}\neg\mathit{green}) \\
\vee\ & \mathbf{G}\neg\mathit{green} \\
\vee\ & \mathbf{GF}((\mathit{green} \wedge (\neg\mathit{blue}\,\mathcal{U}\,\mathit{red}))
\end{aligned}
$$

Specification



Deterministic Parity Automaton

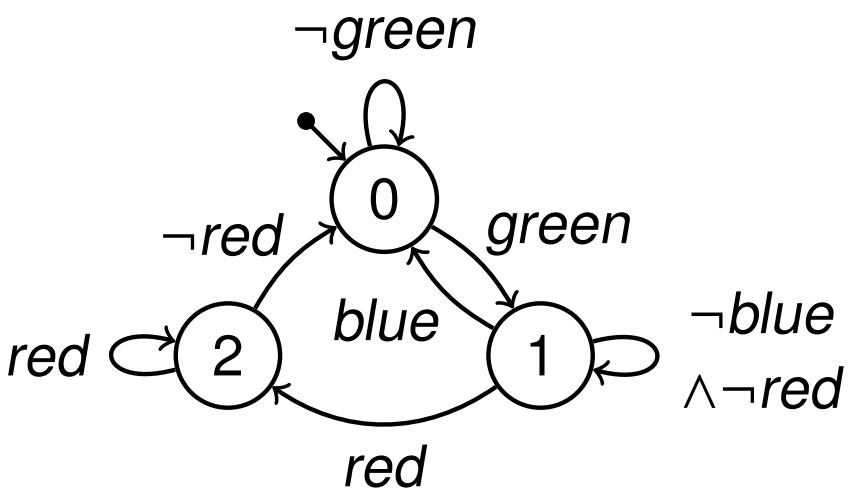
Declaring goals (2)



Definition of parity acceptance

A parity automaton accepts a trace if the highest color that occurs infinitely often along the automaton's run for the trace is **even**.

Declaring goals (2)



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So what are possible goals to be reached?

Colors 0 and 2.

Declaring goals (3)

Main idea

We require the system to decrease goal colors at most k times (for some $k \in \mathbb{N}$), and whenever an odd-colored state is visited, the goal color must be higher than the odd color.

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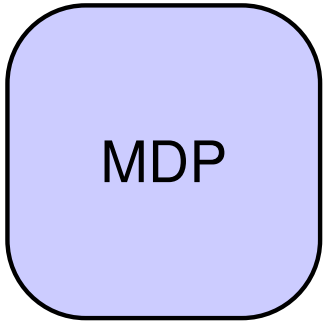
Effect

All infinite traces satisfying this new condition satisfy the original parity objective as well.

Overall workflow



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Overall workflow

MDP

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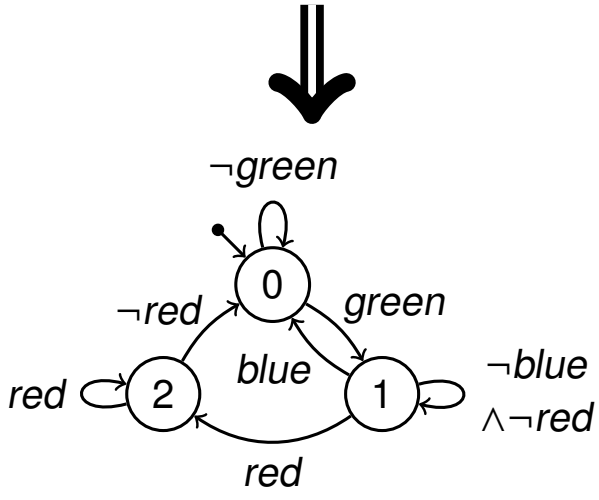

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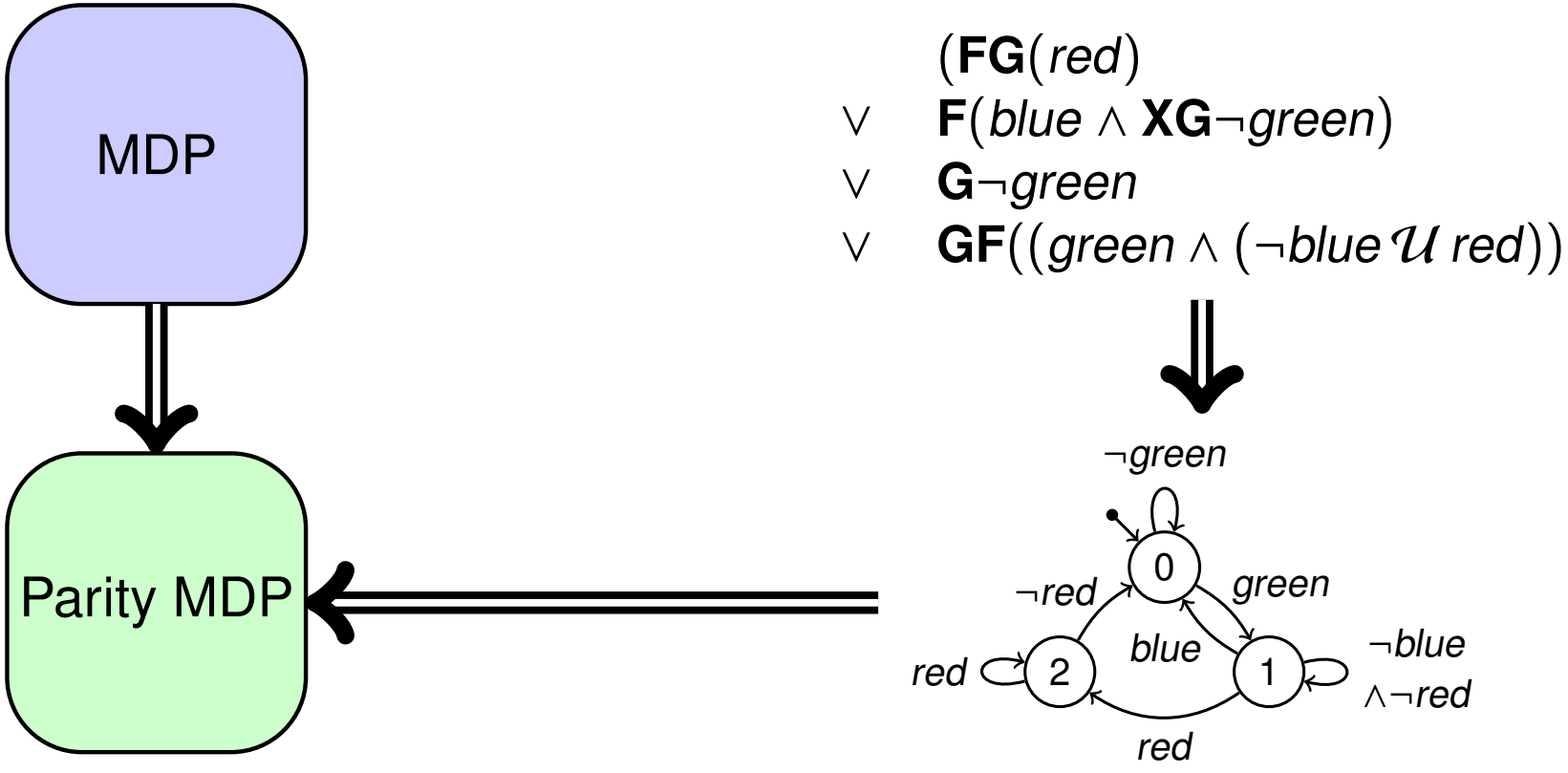

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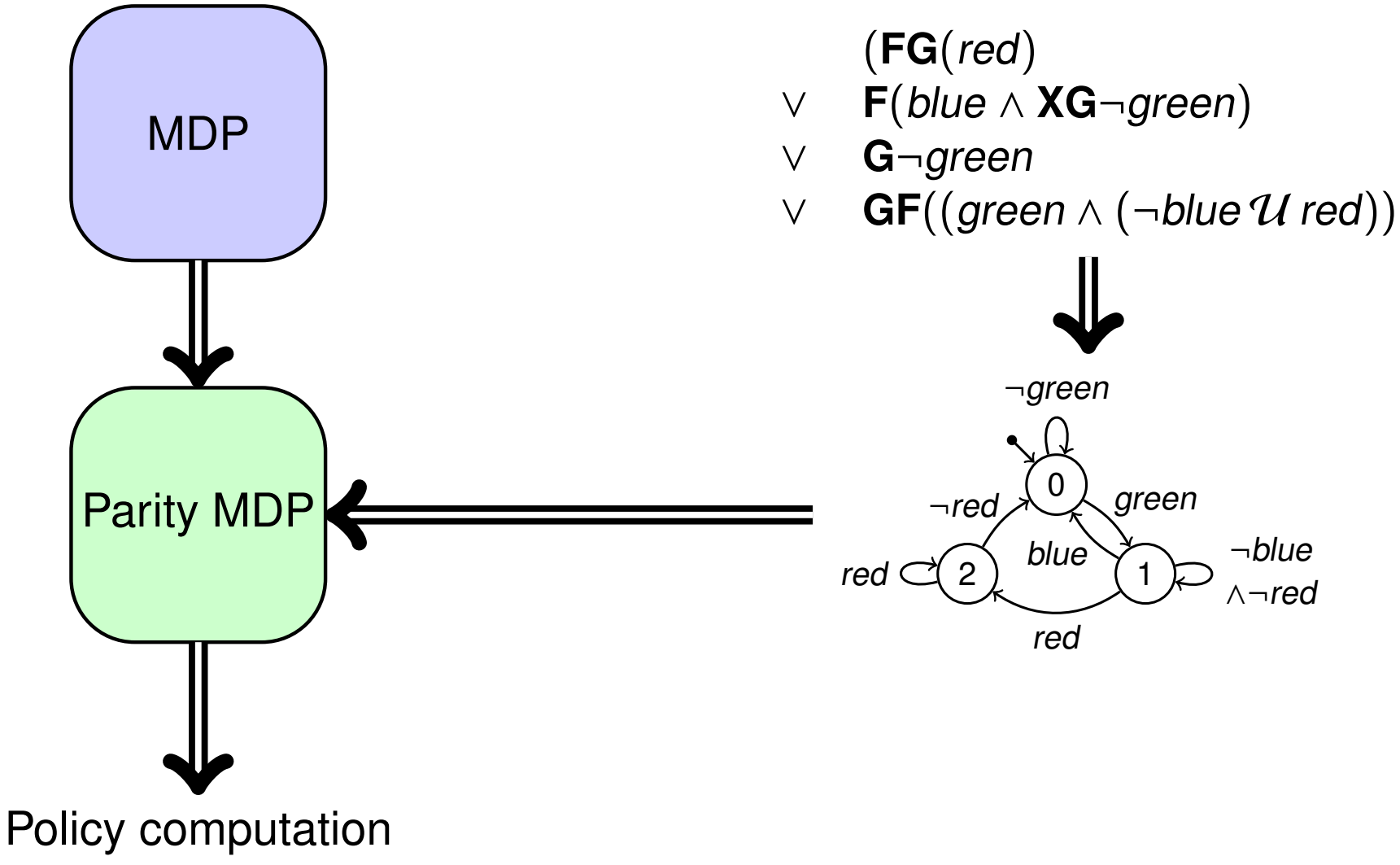

What exactly is now being computed?

We compute for some values of p and k ...

A **control policy** for a **parity MDP** that always declares its respective next goal such that:

- From every goal state, the next goal state is visited with probability at least p.
- Goal states have an even color, and the color of the goal states can only be decreased at most k times along a trace
- The goal color is always greater than or equal to the odd colors of the states visited on along the trace

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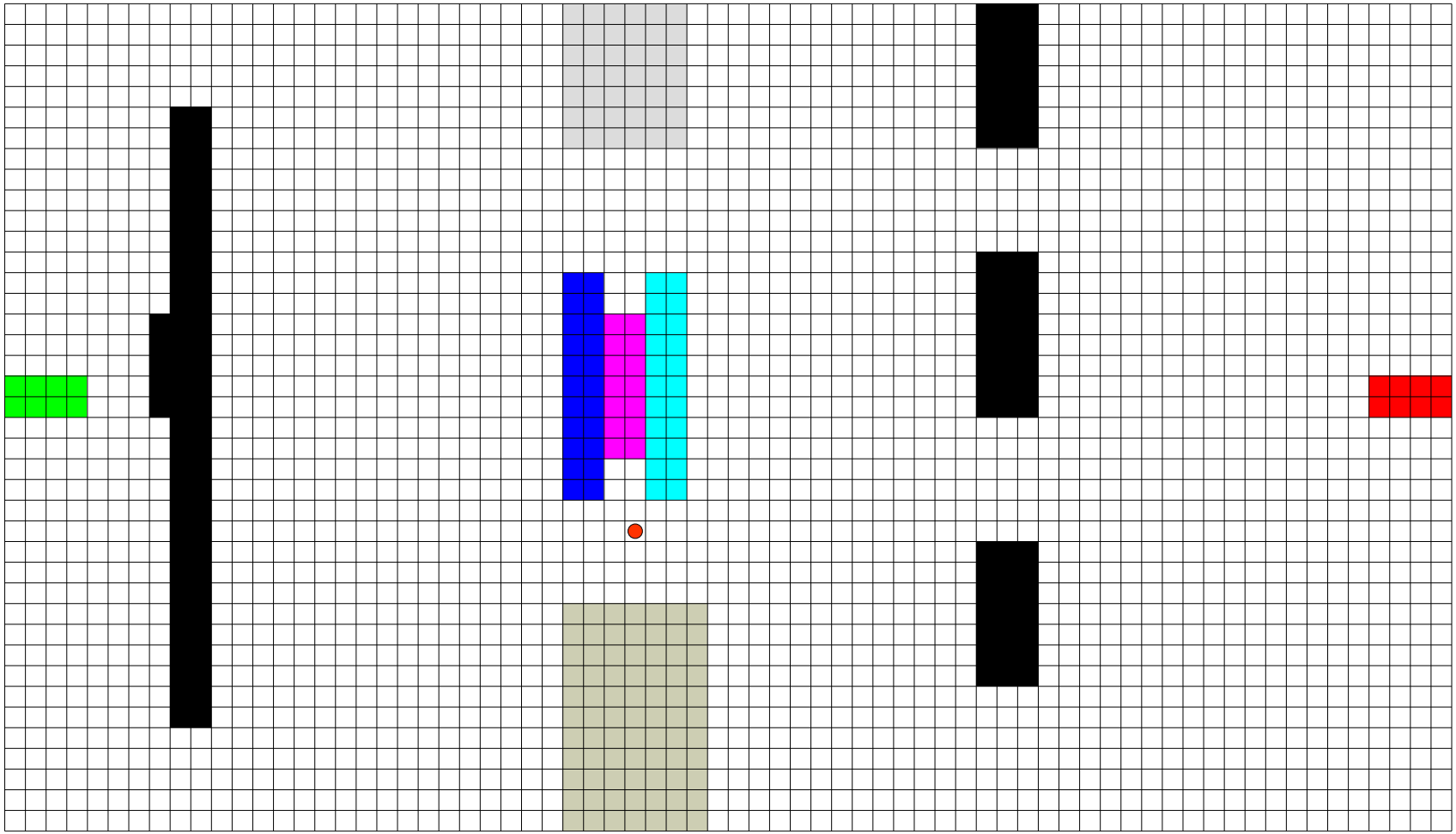
Computing the *best* policies

We perform bisection search over p and compute if there is a k such there exists a *p-risk-averse policy*.

Motivational example problem (revisited)



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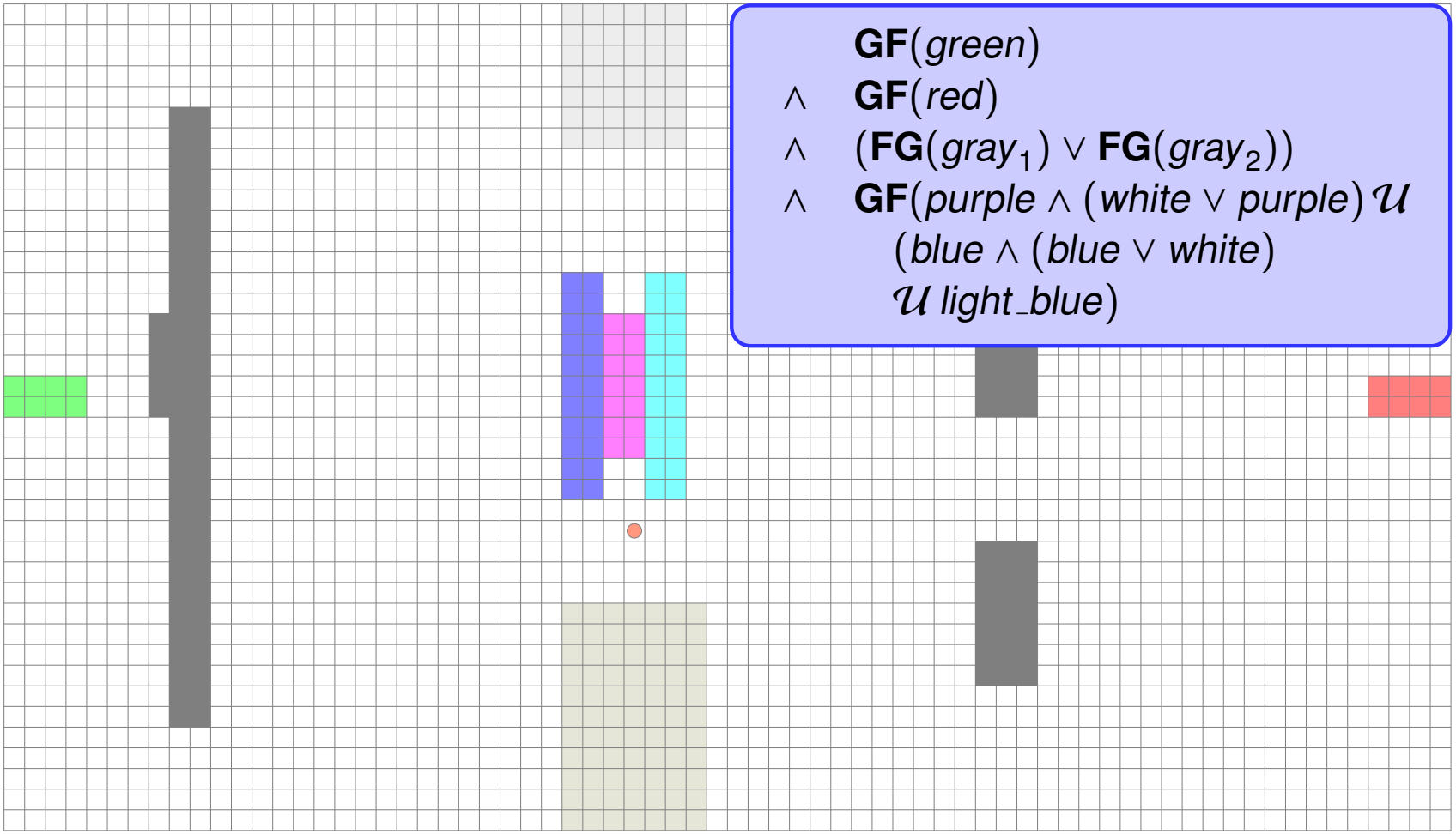

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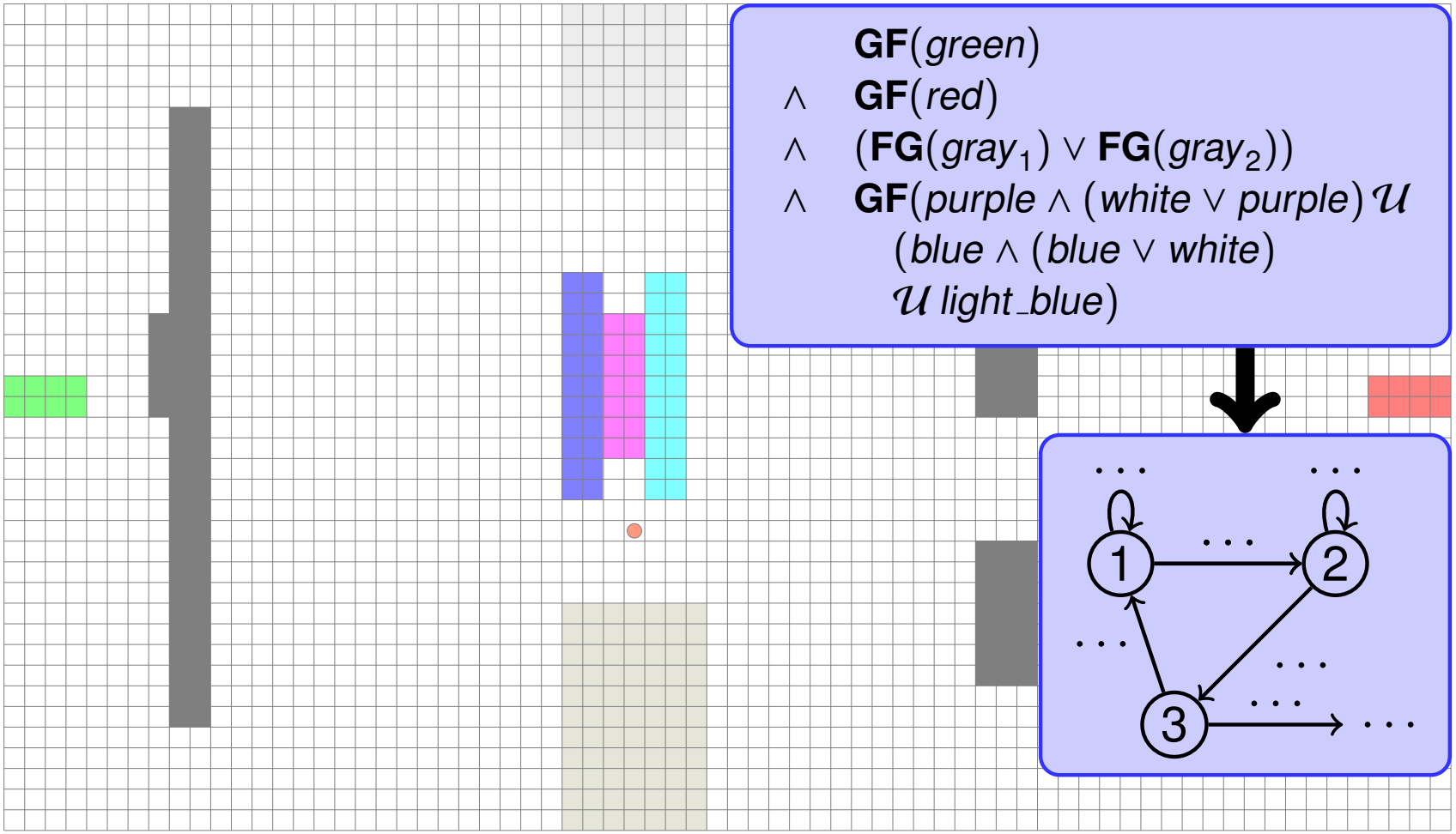

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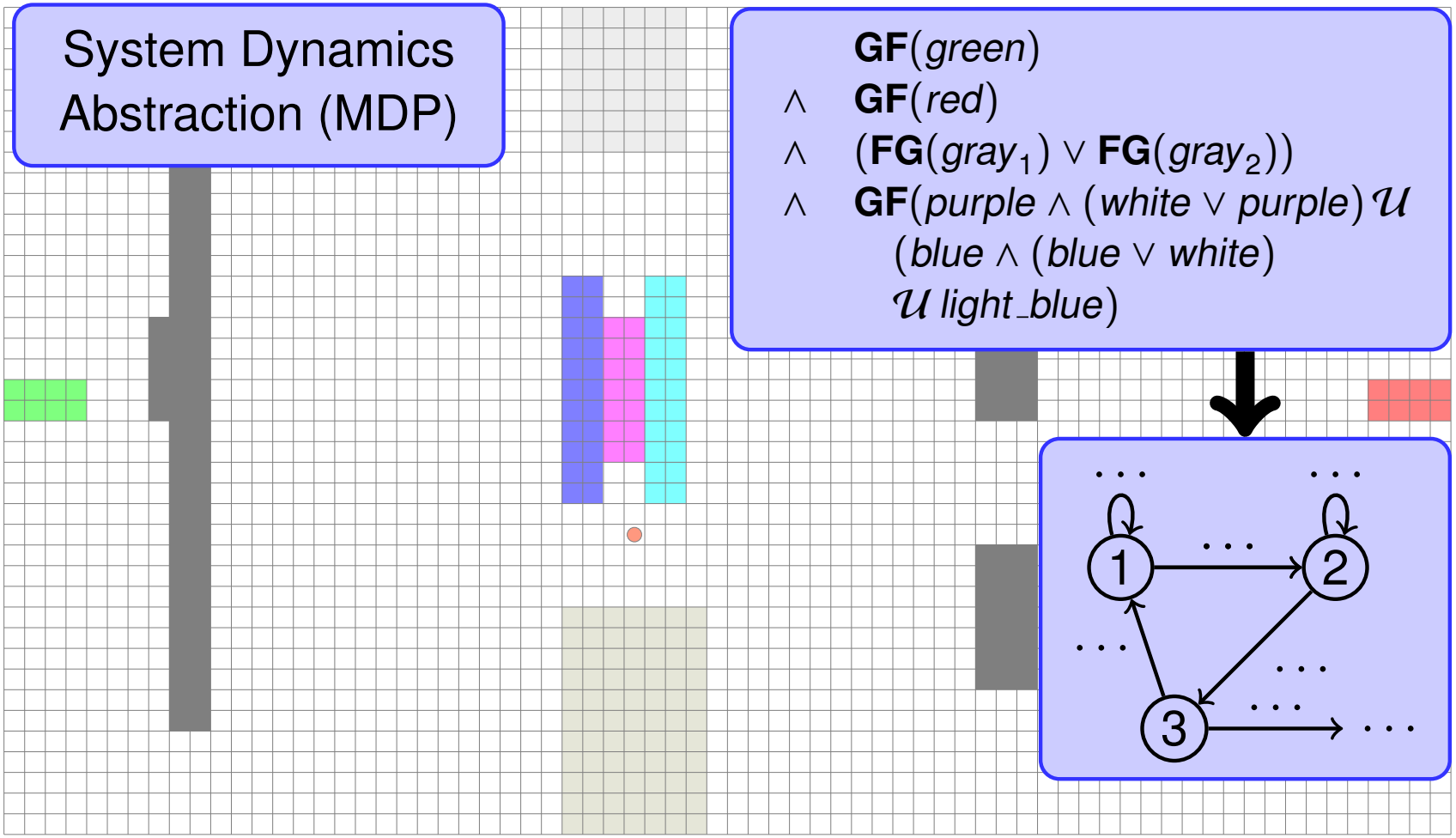

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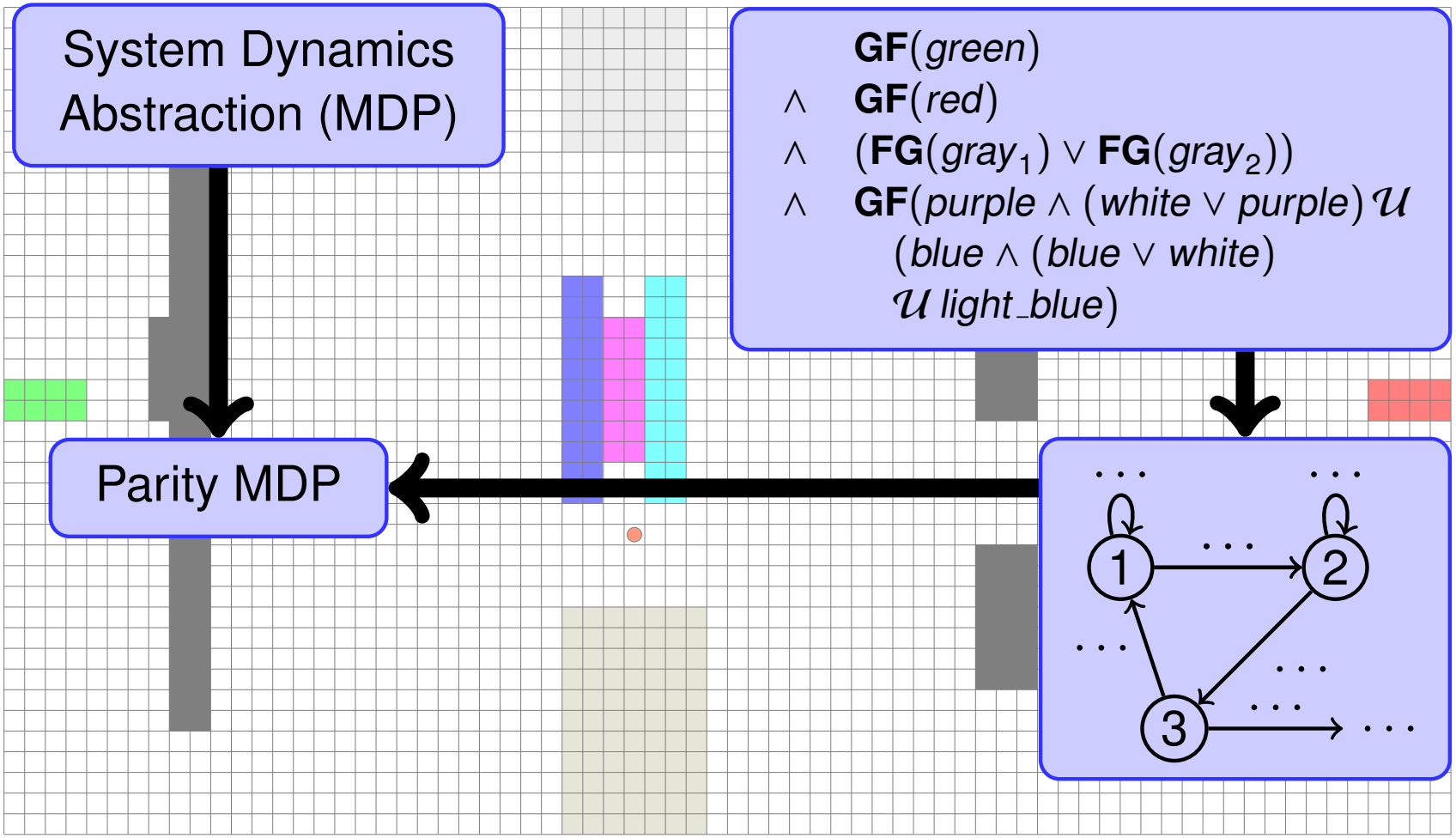

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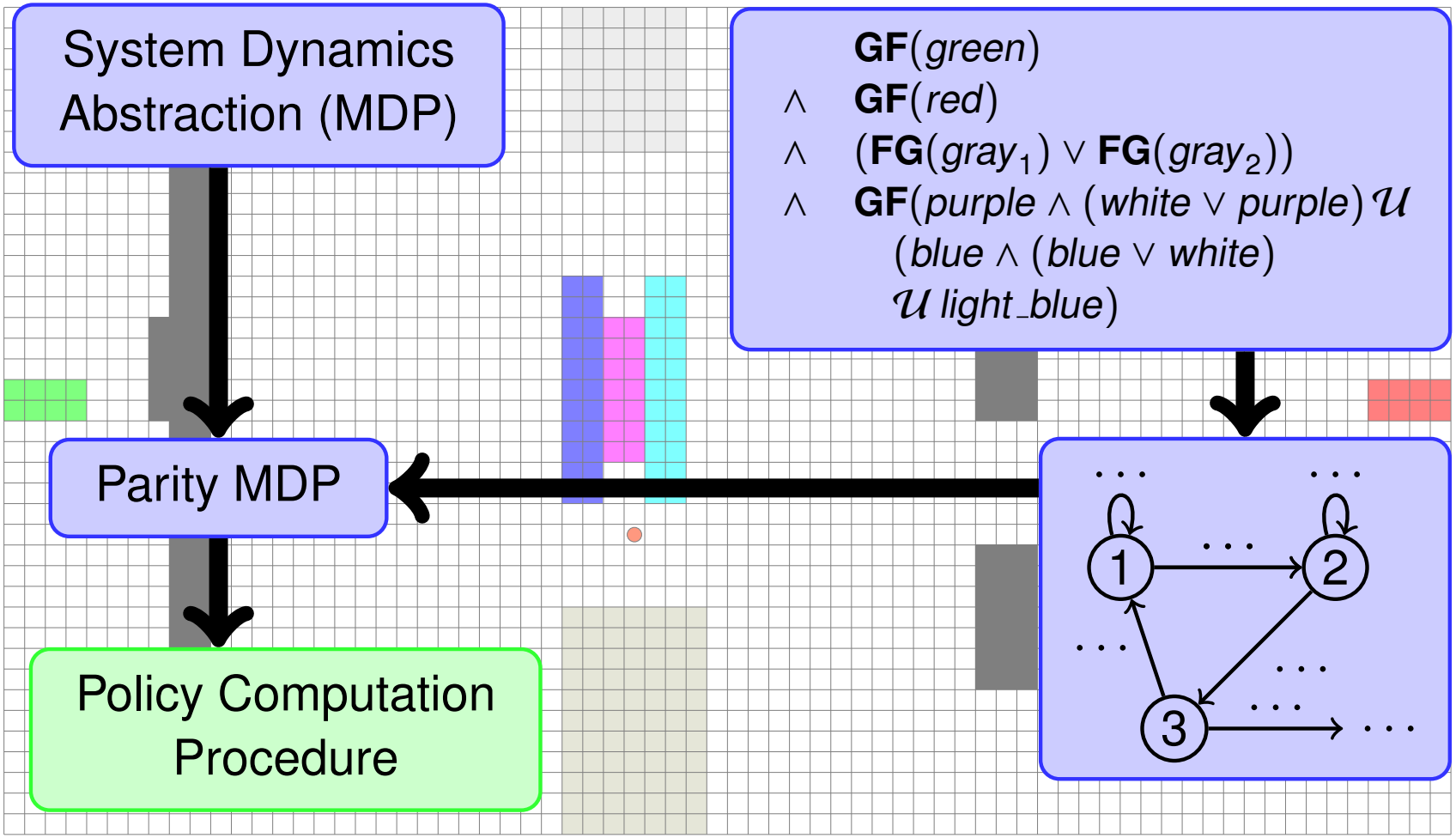

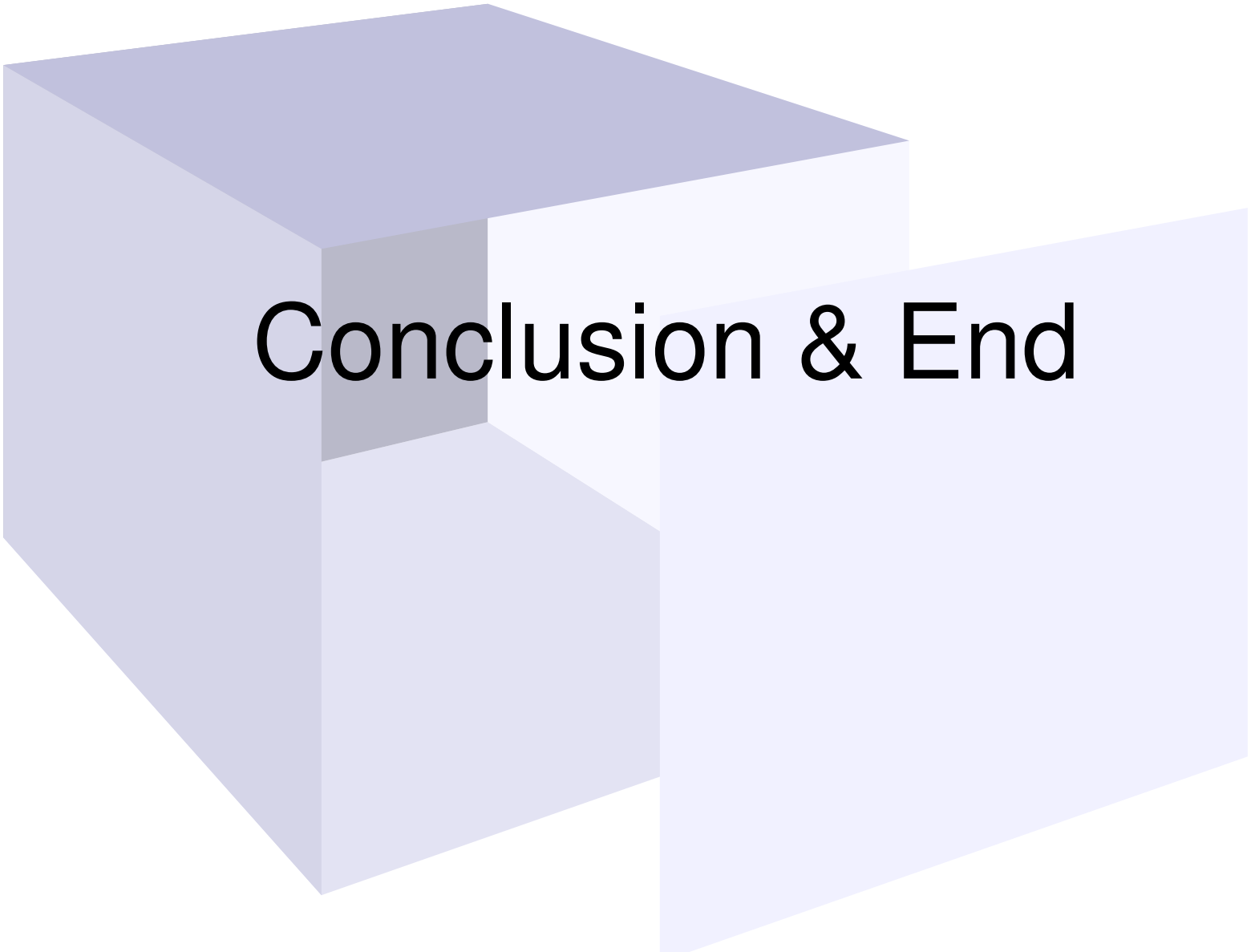

Conclusion & End

Conclusion

p-risk-averse policies

- They allow to find reasonable policies even if the specification cannot be fulfilled in the long run.
- Work with all ω-regular specifications
- Computation can be done efficiently
- Tool available: `http://progirep.github.io/ramps/`

Future work

What about 2.5 player games? Combination with costs?

References I

Maria Svorenova, Ivana Cerna, and Calin Belta. Optimal control of MDPs with temporal logic constraints. In *52nd IEEE Conference on Decision and Control (CDC)*, pages 3938–3943, 2013.

Computing a p-risk-averse policy

Approach in the paper

- For every $p \in [0, \ldots, 1]$, a p-risk-averse control policy has a finite number of states.
- Optimal strategies can be computed by solving a series of optimal reachability policy computations in MDPs.

Formal definition

Definition: p-risk-averse strategy

Let $\mathcal{M} = (S, A, \Sigma, P, C, s_0)$ be a parity MDP. We say that some control policy $f : S^* \to A$ has a *risk-averseness probability* $p \in [0, 1]$ if there exist labelings $l : S^* \to \mathbb{N}$ and $l' : S^* \to \mathbb{B}$ and a Markov chain $\mathcal{C}'$ induced by $\mathcal{M}$ and f with the following properties:

- There exists some number $k \in \mathbb{N}$ such that for all $t_0 t_1 t_2 \ldots \in S^\omega$, there are at most k many indices $i \in \mathbb{N}$ for which we have $l(t_0 \ldots t_i) > l(t_0 \ldots t_i t_{i+1})$.
- For all $t_0 t_1 \ldots t_n \in S^*$, we have that $l(t_0 \ldots t_n)$ is even, and $l'(t_0 \ldots t_n) = \mathbf{tt}$ implies that $C(t_n) \geq l(t_0 \ldots t_n)$ and that $C(t_n)$ is even.
- For all $t_0 t_1 \ldots t_n \in S^*$, if $C(t_n)$ is odd, then $l(t_0 \ldots t_n) > C(t_n)$.
- For all $t = t_0 t_1 \ldots t_n \in S^*$ with either (a) $l'(t) = \mathbf{tt}$ or (b) $t = s_0$, the probability measure in $\mathcal{C}'$ to reach some state $t\, t'_0 \ldots t'_m \in S^*$ with $l'(t\, t'_0 \ldots t'_m) = \mathbf{tt}$ from state t is at least p.