PrIC3: Property Directed Reachability for MDPs

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Abstract. IC3 has been a leap forward in symbolic model checking. This paper proposes PrIC3 (pronounced pricy-three), a conservative extension of IC3 to symbolic model checking of MDPs. Our main focus is to develop the theory underlying PrIC3. Alongside, we present a first implementation of PrIC3 including the key ingredients from IC3 such as generalization, repushing, and propagation.

1 Introduction

IC3. Also known as property-directed reachability (PDR) [22], IC3 [12] is a symbolic approach for verifying finite transition systems (TSSs) against safety properties like “bad states are unreachable”. It combines bounded model checking (BMC) [11] and inductive invariant generation. Put shortly, IC3 either proves that a set $B$ of bad states is unreachable by finding a set of non-$B$ states closed under reachability—called an inducive invariant—or refutes reachability of $B$ by a counterexample path reaching $B$. Rather than unrolling the transition relation (as in BMC), IC3 attempts to incrementally strengthen the invariant “no state in $B$ is reachable” into an inductive one. In addition, it applies aggressive abstraction to the explored state space, so-called generalization [35]. These aspects together with the enormous advances in modern SAT solvers have led to IC3’s success. IC3 has been extended [37,26] and adapted to software verification [18,43]. This paper develops a quantitative IC3 framework for probabilistic models.

MDPs. Markov decision processes (MDPs) extend TSSs with discrete probabilistic choices. They are central in planning, AI as well as in modeling randomized distributed algorithms. A key question in verifying MDPs is quantitative reachability: “is the (maximal) probability to reach $B$ at most $\lambda$?”. Quantitative reachability [50] reduces to solving linear programs (LPs). Various tools support MDP model checking, e.g., Prism [42], Storm [21], modest [33], and EPMC [30]. The LPs are mostly solved using (variants of) value iteration [27,8,50,34]. Symbolic BDD-based MDP model checking originated two decades ago [4] and is rather successful.

Towards IC3 for MDPs. Despite the success of BDD-based symbolic methods in tools like Prism, IC3 has not penetrated probabilistic model checking yet. The success of IC3

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and the importance of quantitative reachability in probabilistic model checking raises the question whether and how IC3 can be adapted—not just utilized—to reason about quantitative reachability in MDPs. This paper addresses the challenges of answering this question. It extends IC3 in several dimensions to overcome these hurdles, making PrIC3 to our knowledge—the first IC3 framework for quantitative reachability in MDPs.⁵ Notably, PrIC3 is conservative: For a threshold λ = 0, PrIC3 solves the same qualitative problem and behaves (almost) the same as standard IC3. Our main contribution is developing the theory underlying PrIC3, which is accompanied by a proof-of-concept implementation.

Challenge 1 (Leaving the Boolean domain). IC3 iteratively computes frames, which are over-approximations of sets of states that can reach B in a bounded number of steps. For MDPs, Boolean reachability becomes a quantitative reachability probability. This requires a shift: frames become real-valued functions rather than sets of states. Thus, there are infinitely many possible frames—even for finite-state MDPs—just as for infinite-state software [18,43] and hybrid systems [53]. Additionally, whereas in TSs a state reachable within k steps remains reachable on increasing k, the reachability probability in MDPs may increase. This complicates ensuring termination of an IC3 algorithm for MDPs. △

Challenge 2 (Counterexamples ≠ single paths). For TSs, a single cycle-free path [6] to B suffices to refute that “B is not reachable”. This is not true in the probabilistic setting [31]. Instead, proving that the probability of reaching B exceeds the threshold λ requires a set of possibly cyclic paths—e.g., represented as a sub-MDP [14]—whose probability mass exceeds λ. Handling sets of paths as counterexamples in the context of IC3 is new. △

Challenge 3 (Strengthening). This key IC3 technique intuitively turns a proof obligation of type (i) “state s is unreachable from the initial state sI” into type (ii) “s’s predecessors are unreachable from sI”. A first issue is that in the quantitative setting, the standard characterization of reachability probabilities in MDPs (the Bellman equations) inherently reverses the direction of reasoning (cf. “reverse” IC3 [52]): Hence, strengthening turns (i) “s cannot reach B” into (ii) “s’s successors cannot reach B”.

A much more challenging issue, however, is that in the quantitative setting obligations of type (i) read “s is reachable with at most probability δ”. However, the strengthened type (ii) obligation must then read: “the weighted sum over the reachability probabilities of the successors of s is at most δ”. In general, there are infinitely many possible choices of subobligations for the successors of s in order to satisfy the original obligation, because—grossly simplified—there are infinitely many possibilities for a and b to satisfy weighted sums such as 1/3a + 1/3b ≤ δ. While we only need one choice of subobligations, picking a good one is approximately as hard as solving the entire problem altogether. We hence require a heuristic, which is guided by a user-provided oracle. △

Challenge 4 (Generalization). “One of the key components of IC3 is [inductive] generalization” [12]. Generalization [35] abstracts single states. It makes IC3 scale, but is not

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⁵ Recently, (standard) IC3 for TSs was utilized in model checking Markov chains [48] to on-the-fly compute the states that cannot reach B.

⁶ In [37], tree-like counterexamples are used for non-linear predicate transformers in IC3.
essential for correctness. To facilitate generalization, systems should be encoded symbolically, i.e., integer-valued program variables describe states. Frames thus map variables to probabilities. A first aspect is how to effectively present them to an SMT-solver. Conceptually, we use uninterpreted functions and universal quantifiers (encoding program behavior) together with linear real arithmetic to encode the weighted sums occurring when reasoning about probabilities. A second aspect is more fundamental: Abstractly, IC3’s generalization guesses an unreachable set of states. We, however, need to guess this set and a probability for each state. To be effective, these guesses should moreover eventually yield an inductive frame, which is often highly nonlinear. We propose three SMT-guided interpolation variants for guessing these maps.

Structure of this paper. We develop PrIC3 gradually: We explain the underlying rationale in Sect. 3. We also describe the core of PrIC3—called PrIC3_H—which resembles closely the main loop of standard IC3, but uses adapted frames and termination criteria (Chall. 1). In line with Chall. 3, PrIC3_H is parameterized by a heuristic \( \mathcal{H} \) which is applied whenever we need to select one out of infinitely many probabilities. No requirements on the quality of \( \mathcal{H} \) are imposed. PrIC3_H is sound and always terminates: If it returns true, then the maximal reachability probability is bounded by \( \lambda \). Without additional assumptions about \( \mathcal{H} \), PrIC3_H is incomplete: on returning false, it is unknown whether the returned subMDP is indeed a counterexample (Chall. 2). Sect. 4 details strengthening (Chall. 3). Sect. 5 presents a sound and complete algorithm PrIC3 on top of PrIC3_H. Sect. 6 presents a prototype, discusses our chosen heuristics, and addresses Chall. 4. Sect. 7 shows some encouraging experiments, but also illustrates need for further progress.

Related Work. Just like IC3 has been a symbiosis of different approaches, PrIC3 has been inspired by several existing techniques from the verification of probabilistic systems.

BMC. Adaptions of BMC to Markov chains (MCs) with a dedicated treatment of cycles have been pursued in \cite{56}. The encoding in \cite{23} annotates sub-formulae with probabilities. The integrated SAT solving process implicitly unrolls all paths leading to an exponential blow-up. In \cite{51}, this is circumvented by grouping paths, discretizing them, and using an encoding with quantifiers and bit-vectors, but without numerical values. Recently, \cite{55} extends this idea to a PAC algorithm by purely propositional encodings and (approximate) model counting \cite{16}. These approaches focus on MCs and are not mature yet.

Invariant synthesis. Quantitative loop invariants are key in analyzing probabilistic programs whose operational semantics are (possibly infinite) MDPs \cite{25}. A quantitative invariant \( I \) maps states to probabilities. \( I \) is shown to be an invariant by comparing \( I \) to the result of applying the MDP’s Bellman operator to \( I \). Existing approaches for invariant synthesis are, e.g., based on weakest pre-expectations \cite{41,33,28,32}, template-based constraint solving \cite{24}, notions of martingales \cite{15,9,3,54}, and solving recurrence relations \cite{10}. All but the last technique require user guidance.

Abstraction. To combat state-space explosion, abstraction is often employed. CEGAR for MDPs \cite{56} deals with explicit sets of paths as counterexamples. Game-based abstraction \cite{40,29} and partial exploration \cite{13} exploit that not all paths have to be explored to prove bounds on reachability probabilities.
Statistical methods and (deep) reinforcement learning. Finally, an avenue that avoids storing a (complete) model are simulation-based approaches (statistical model checking [2]) and variants of reinforcement learning, possibly with neural networks. For MDPs, these approaches yield weak statistical guarantees [19], but may provide good oracles.

2 Problem Statement

Our aim is to prove that the maximal probability of reaching a set \( B \) of bad states from the initial state \( s_I \) of a Markov decision process \( \mathcal{M} \) is at most some threshold \( \lambda \). Below, we give a formal description of our problem. We refer to [49,7] for a thorough introduction.

Definition 1 (MDPs). A Markov decision process (MDP) is a tuple \( \mathcal{M} = (S, s_I, \text{Act}, P) \), where \( S \) is a finite set of states, \( s_I \in S \) is the initial state, \( \text{Act} \) is a finite set of actions, and \( P : S \times \text{Act} \times S \to [0,1] \) is a transition probability function. For state \( s \), let \( \text{Act}(s) = \{ a \in \text{Act} \mid \exists s' \in S : P(s,a,s') > 0 \} \) be the enabled actions at \( s \). For all states \( s \in S \), we require \( |\text{Act}(s)| \geq 1 \) and \( \sum_{s' \in S} P(s,a,s') = 1 \).

For this paper, we fix an MDP \( \mathcal{M} = (S, s_I, \text{Act}, P) \), a set of bad states \( B \subseteq S \), and a threshold \( \lambda \in [0,1] \). The maximal (unbounded) reachability probability to eventually reach a state in \( B \) from a state \( s \) is denoted by \( \Pr^{\max}(s \models \Diamond B) \). We characterize \( \Pr^{\max}(s \models \Diamond B) \) using the so-called Bellman operator. Let \( M^N \) denote the set of functions from \( N \) to \( M \). Anticipating IC3 terminology, we call a function \( F \in [0,1]^{S} \) a frame. We denote by \( F[s] \) the evaluation of frame \( F \) for state \( s \).

Definition 2 (Bellman Operator). For a set of actions \( A \subseteq \text{Act} \), we define the Bellman operator for \( A \) as a frame transformer \( \Phi_A : [0,1]^S \to [0,1]^S \) with

\[
\Phi_A(F)[s] = \begin{cases} 
1, & \text{if } s \in B \\
\max_{a \in A} \sum_{s' \in S} P(s,a,s') \cdot F[s'] , & \text{if } s \notin B .
\end{cases}
\]

We write \( \Phi_a \) for \( \Phi_{\{a\}} \), \( \Phi \) for \( \Phi_{\text{Act}} \), and call \( \Phi \) simply the Bellman operator.

For every state \( s \), the maximal reachability probability \( \Pr^{\max}(s \models \Diamond B) \) is then given by the least fixed point of the Bellman operator \( \Phi \). That is,

\[
\forall s : \quad \Pr^{\max}(s \models \Diamond B) = (\lfp \Phi)[s] ,
\]

where the underlying partial order on frames is a complete lattice with ordering

\[
F_1 \leq F_2 \iff \forall s \in S : F_1[s] \leq F_2[s] .
\]

In terms of the Bellman operator, our formal problem statement reads as follows:

Given an MDP \( \mathcal{M} \) with initial state \( s_I \), a set \( B \) of bad states, and a threshold \( \lambda \in [0,1] \),

prove or refute that \( \Pr^{\max}(s_I \models \Diamond B) = (\lfp \Phi)[s_I] \leq \lambda \).
Whenever $\Pr_{\text{max}}(s_I \models \Diamond B) \leq \lambda$ indeed holds, we say that the MDP $\mathfrak{M}$ is safe (with respect to the set of bad states $B$ and threshold $\lambda$); otherwise, we call it unsafe.

**Recovery Statement 1.** For $\lambda = 0$, our problem statement is equivalent to the qualitative reachability problem solved by (reverse) standard IC3, i.e., prove or refute that all bad states in $B$ are unreachable from the initial state $s_I$.

**Example 1.** The MDP $\mathfrak{M}$ in Fig. 1 consists of 6 states with initial state $s_0$ and bad states $B = \{s_5\}$. In $s_2$, actions $a$ and $b$ are enabled; in all other states, one unlabeled action is enabled. We have $\Pr_{\text{max}}(s_0 \models \Diamond B) = \frac{2}{3}$. Hence, $\mathfrak{M}$ is safe for all thresholds $\lambda \geq \frac{2}{3}$ and unsafe for $\lambda < \frac{2}{3}$. In particular, $\mathfrak{M}$ is unsafe for $\lambda = 0$ as $s_5$ is reachable from $s_0$. △

## 3 The Core $\PrIC$ Algorithm

The purpose of PrIC3 is to prove or refute that the maximal probability to reach a bad state in $B$ from the initial state $s_I$ of the MDP $\mathfrak{M}$ is at most $\lambda$. In this section, we explain the rationale underlying PrIC3. Moreover, we describe the core of PrIC3—called PrIC3$\mathcal{H}$—which bears close resemblance to the main loop of standard IC3 for TSs.

Because of the inherent direction of the Bellman operator, we build PrIC3 on reverse IC3 [52], cf. Chall. 3. Reversing constitutes a shift from reasoning along the direction initial-to-bad to bad-to-initial. While this shift is mostly inessential to the fundamentals underlying IC3, the reverse direction is unswayable in the probabilistic setting. Whenever we draw a connection to standard IC3, we thus generally mean reverse IC3.

### 3.1 Inductive Frames

IC3 for TSs operates on (qualitative) frames representing sets of states of the TS at hand. A frame $F$ can hence be thought of as a mapping from states to $\{0, 1\}$. In PrIC3 for MDPs, we need to move from a Boolean to a quantitative regime. Hence, a (quantitative) frame is a mapping from states to probabilities in $[0, 1]$.

For a given TS, consider the frame transformer $T$ that adds to a given input frame $F'$ all bad states in $B$ and all predecessors of the states contained in $F'$. The rationale of standard (reverse) IC3 is to find a frame $F \in \{0, 1\}^S$ such that (i) the initial state $s_I$ does not belong to $F$ and (ii) applying $T$ takes us down in the partial order on frames, i.e.,

\[(i) \ F[s_I] = 0 \quad \text{and} \quad (ii) \ T(F) \leq F.\]

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\[\text{In IC3, frames are typically characterized by logical formulae. To understand IC3’s fundamental principle, however, we prefer to think of frames as functions in } \{0, 1\}^S \text{ partially ordered by}\ \leq.\]
Intuitively, (i) postulates the hypothesis that \( s_I \) cannot reach \( B \) and (ii) expresses that \( F \) is closed under adding bad states and taking predecessors, thus affirming the hypothesis.

Analogously, the rationale of \( \text{PrI} \text{C}3 \) is to find a frame \( F \in [0, 1]^S \) such that (i) \( F \) postulates that the probability of \( s_I \) to reach \( B \) is at most the threshold \( \lambda \) and (ii) applying the Bellman operator \( \Phi \) to \( F \) takes us down in the partial order on frames, i.e.,

\[
(i) \quad F[s_I] \leq \lambda \quad \text{and} \quad (ii) \quad \Phi(F) \leq F.
\]

Frames satisfying the above conditions are called inductive invariants in \( \text{IC}3 \). We adopt this terminology. By Park’s Lemma \([47]\), which in our setting reads

\[
\Phi(F) \leq F \quad \text{implies} \quad \text{lfp}(\Phi) \leq F,
\]

an inductive invariant \( F \) would indeed witness that \( \text{Pr}^{\text{max}}(s_I \models \Diamond B) \leq \lambda \), because

\[
\text{Pr}^{\text{max}}(s_I \models \Diamond B) = (\text{lfp}(\Phi))[s_I] \leq F[s_I] \leq \lambda.
\]

If no inductive invariant exists, then standard \( \text{IC}3 \) will find a counterexample: a path from the initial state \( s_I \) to a bad state in \( B \), which serves as a witness to refute. Analogously, \( \text{PrI} \text{C}3 \) will find a counterexample, but of a different kind: Since single paths are insufficient as counterexamples in the probabilistic realm (Chall. 2), \( \text{PrI} \text{C}3 \) will instead find a subsystem of states of the MDP witnessing \( \text{Pr}^{\text{max}}(s_I \models \Diamond B) > \lambda \).

### 3.2 The \( \text{PrI} \text{C}3 \) Invariants

Analogously to standard \( \text{IC}3 \), \( \text{PrI} \text{C}3 \) aims to find the inductive invariant by maintaining a sequence of frames \( F_0 \leq F_1 \leq F_2 \leq \ldots \) such that \( F_i[s] \) overapproximates the maximal probability of reaching \( B \) from \( s \) within at most \( i \) steps. This \( i \)-step-bounded reachability probability \( \text{Pr}^{\text{max}}(s \models \Diamond^i B) \) can be characterized using the Bellman operator: \( \Phi(\Phi(0)) \) is the 0-step probability; it is 1 for every \( s \in B \) and 0 otherwise. For any \( i \geq 0 \), we have

\[
\text{Pr}^{\text{max}}(s \models \Diamond^i B) = (\Phi^i(\Phi(0)))[s] = (\Phi^{i+1}(0))[s],
\]

where \( 0 \), the frame that maps every state to 0, is the least frame of the underlying complete lattice. For a finite MDP, the unbounded reachability probability is then given by the limit

\[
\text{Pr}^{\text{max}}(s \models \Diamond B) = (\text{lfp}(\Phi))[s] = \left( \lim_{n \to \infty} \Phi^n(0) \right)[s] = \lim_{n \to \infty} \text{Pr}^{\text{max}}(s \models \Diamond^n B),
\]

where \((*)\) is a consequence of the well-known Kleene fixed point theorem \([44]\).

The sequence \( F_0 \leq F_1 \leq F_2 \leq \ldots \) maintained by \( \text{PrI} \text{C}3 \) should frame-wise overapproximate the increasing sequence \( \Phi(0) \leq \Phi^2(0) \leq \Phi^3(0) \ldots \). Pictorially:

\[
\begin{align*}
F_0 & \leq F_1 & \leq F_2 & \leq \ldots & \leq F_k \\
\Phi(0) & \leq \Phi^2(0) & \leq \Phi^3(0) & \leq \ldots & \leq \Phi^{k+1}(0)
\end{align*}
\]
However, the sequence $\Phi(0)$, $\Phi^2(0)$, $\Phi^3(0)$, ... will never explicitly be known to PrIC3. Instead, PrIC3 will ensure the above frame-wise overapproximation property implicitly by enforcing the so-called PrIC3 invariants on the frame sequence $F_0$, $F_1$, $F_2$, ... . Apart from allowing for a threshold $0 \leq \lambda \leq 1$ on the maximal reachability probability, these invariants coincide with the standard IC3 invariants (where $\lambda = 0$ is fixed). Formally:

**Definition 3 (PrIC3 Invariants).** Frames $F_0$, ..., $F_k$, for $k \geq 0$, satisfy the PrIC3 invariants, a fact we will denote by $\PrIC3_{\text{inv}}(F_0, \ldots, F_k)$, if all of the following hold:

1. **Initiality:** $F_0 = \Phi(0)$
2. **Chain Property:** $\forall 0 \leq i < k : F_i \leq F_{i+1}$
3. **Frame-safety:** $\forall 0 \leq i \leq k : F_i[s_I] \leq \lambda$
4. **Relative Inductivity:** $\forall 0 \leq i < k : \Phi(F_i) \leq F_{i+1}$

The PrIC3 invariants enforce the above picture: The chain property ensures $F_0 \leq F_1 \leq \ldots \leq F_k$. We have $\Phi(0) = F_0 \leq F_0$ by initiality. Assuming $\Phi^{i+1}(0) \leq F_i$ as induction hypothesis, monotonicity of $\Phi$ and relative inductivity imply $\Phi^{i+2}(0) \leq \Phi(F_i) \leq F_{i+1}$.

By overapproximating $\Phi(0)$, $\Phi^2(0)$, $\ldots$, $\Phi^k(0)$, the frames $F_0$, $\ldots$, $F_k$ in effect bound the maximal step-bounded reachability probability of every state:

**Lemma 1.** Let frames $F_0$, $\ldots$, $F_k$ satisfy the PrIC3 invariants. Then

$$\forall s \forall i \leq k : \Pr^{\max}(s \models \diamond B) \leq F_i[s].$$

In particular, Lem. 1 together with frame-safety ensures that the maximal step-bounded reachability probability of the initial state $s_I$ to reach $B$ is at most the threshold $\lambda$.

As for proving that the unbounded reachability probability is also at most $\lambda$, it suffices to find two consecutive frames, say $F_i$ and $F_{i+1}$, that coincide:

**Lemma 2.** Let frames $F_0$, $\ldots$, $F_k$ satisfy the PrIC3 invariants. Then

$$\exists i < k : F_i = F_{i+1}$$

implies

$$\Pr^{\max}(s_I \models \diamond B) \leq \lambda.$$

**Proof.** $F_i = F_{i+1}$ and relative inductivity yield $\Phi(F_i) \leq F_{i+1} = F_i$, rendering $F_i$ inductive. By Park’s lemma (cf. Section 3.1), we obtain $\lfp \Phi \leq F_i$ and—by frame-safety—conclude

$$\Pr^{\max}(s_I \models \diamond B) = (\lfp \Phi)[s_I] \leq F_i[s_I] \leq \lambda.$$  

\[\square\]

3.3 Operationalizing the PrIC3 Invariants for Proving Safety

Lem. 2 gives us a clear angle of attack for proving an MDP safe: Repeatedly add and refine frames approximating step-bounded reachability probabilities for more and more steps while enforcing the PrIC3 invariants (cf. Def. 3.2) until two consecutive frames coincide.

Analogously to standard IC3, this approach is taken by the core loop PrIC3* depicted in Alg. 1 differences to the main loop of IC3 (cf. [22] Fig. 5) are highlighted in red. A particular difference is that PrIC3* is parameterized by a heuristic $\mathcal{H}$ for finding
Data: MDP $\mathcal{M}$, set of bad states $B$, threshold $\lambda$

Result: true or false and a subset of the states of $\mathcal{M}$

1. $F_0 \leftarrow \Phi(0)$;  $F_1 \leftarrow 1$;  $k \leftarrow 1$;  $oldSubsystem \leftarrow 0$;

2. while true do
3.   success, $F_0, \ldots, F_k$, subsystem $\leftarrow$ Strengthen$_H(F_0, \ldots, F_k)$;
4.   if ~success then return false, subsystem;
5.   $F_{k+1} \leftarrow 1$;
6.   $F_0, \ldots, F_{k+1} \leftarrow$ Propagate $(F_0, \ldots, F_{k+1})$;
7.   if $\exists 1 \leq i \leq k: F_i = F_{i+1}$ then return true, __;
8.   if $oldSubsystem = subsystem$ then return false, subsystem;
9.   $k \leftarrow k + 1$;  $oldSubsystem \leftarrow subsystem$;
10. end

Algorithm 1: PrIC$_3^H$($\mathcal{M}$, $B$, $\lambda$)

suitable probabilities (see Chall. 3). Since the precise choice of $\mathcal{H}$ is irrelevant for the soundness of PrIC$_3^H$, we defer a detailed discussion of suitable heuristics to Sec. 4.

As input, PrIC$_3^H$ takes an MDP $\mathcal{M} = (S, \delta, \mathcal{F}, P)$, a set $B \subseteq S$ of bad states, and a threshold $\lambda \in [0, 1]$. Since the input is never changed, we assume it to be globally available, also to subroutines. As output, PrIC$_3^H$ returns true if two consecutive frames become equal. We hence say that PrIC$_3^H$ is sound if it only returns true if $\mathcal{M}$ is safe.

We will formalize soundness using Hoare triples. For precondition $\phi$, postcondition $\psi$, and program $P$, the triple $\{ \phi \} P \{ \psi \}$ is valid (for partial correctness) if, whenever program $P$ starts in a state satisfying precondition $\phi$ and terminates in some state $s'$, then $s'$ satisfies postcondition $\psi$. Soundness of PrIC$_3^H$ then means validity of the triple

$$\{ true \} safe, __ \leftarrow PrIC_3^H(\mathcal{M}, B, \lambda) \{ safe \Rightarrow Pr^{\max}(\delta | = \emptyset B) = \lambda \}.$$ 

Let us briefly go through the individual steps of PrIC$_3^H$ in Alg. 1 and convince ourselves that it is indeed sound. After that, we discuss why PrIC$_3^H$ terminates and what happens if it is unable to prove safety by finding two equal consecutive frames.

**How PrIC$_3^H$ Works.** Recall that PrIC$_3^H$ maintains a sequence of frames $F_0, \ldots, F_k$ which is initialized in l. 1 with $k = 1$, $F_0 = \Phi(0)$, and $F_1 = 1$, where the frame $1$ maps every state to $1$. Every time upon entering the while-loop in terms l. 2 the initial segment $F_0, \ldots, F_{k-1}$ satisfies all PrIC$_3$ invariants (cf. Def. 3), whereas the full sequence $F_0, \ldots, F_k$ potentially violates frame-safety as it is possible that $F_k[s_f] > \lambda$.

In l. 3 procedure Strengthen$_H$—detailed in Sect. 4—is called to restore all PrIC$_3$ invariants on the entire frame sequence: It either returns true if successful or returns false and a counterexample (in our case a subsystem of the MDP) if it was unable to do so. To ensure soundness of PrIC$_3^H$, it suffices that Strengthen$_H$ restores the PrIC$_3$ invariants whenever it returns true. Formally, Strengthen$_H$ must meet the following specification:
Definition 4. ** Procedure Strengthen₄H** is sound if the following Hoare triple is valid:

\[
\{ \PrIC₃\text{Inv}(F₀, \ldots, F_{k-1}) \land F_{k-1} \leq F_k \land \Phi(F_{k-1}) \leq F_k \} \\
\text{success, } F₀, \ldots, F_k \models \_, \_ \leftarrow \text{Strengthen₄H}(F₀, \ldots, F_k) \\
\{ \text{success } \Rightarrow \PrIC₃\text{Inv}(F₀, \ldots, F_k) \}.
\]

If Strengthen₄H returns true, then a new frame \(F_{k+1} = 1\) is created in l.5. After that, the (now initial) segment \(F₀, \ldots, F_k\) again satisfies all \(\PrIC₃\) invariants, whereas the full sequence \(F₀, \ldots, F_{k+1}\) potentially violates frame-safety at \(F_{k+1}\). **Propagation** (l.6) aims to speed up termination by updating \(F_{i+1}[s]\) by \(F_i[s]\) if this does not violate relative inductivity. Consequently, the previously mentioned properties remain unchanged.

If Strengthen₄H returns false, the \(\PrIC₃\) invariants—premises to Lem.2 for witnessing safety—cannot be restored and \(\PrIC₃\) terminates returning false (l.3). Returning false (also possible in l.5) has by specification no affect on soundness of \(\PrIC₃\)₄H.

In l.7 we check whether there exist two identical consecutive frames. If so, Lem.2 yields that the MDP is safe; consequently, \(\PrIC₃\)₄H returns true. Otherwise, we increment \(k\) and are in the same setting as upon entering the loop, now with an increased frame sequence; \(\PrIC₃\)₄H then performs another iteration. In summary, we obtain:

**Theorem 1 (Soundness of \(\PrIC₃\)₄H).** If Strengthen₄H is sound and Propagate does not affect the \(\PrIC₃\) invariants, then \(\PrIC₃\)₄H is sound, i.e., the following triple is valid:

\[
\{ \text{true } \} \models \text{safe, } \_ \leftarrow \PrIC₃\text{₄H}(\emptyset, B, \lambda) \{ \text{safe } \Rightarrow \PrIC₃\text{max}(s₁ \models \emptyset B) \leq \lambda \}
\]

**PrIC₃₄H terminates for unsafe MDPs.** If the MDP is unsafe, then there exists a step-bound \(n\), such that \(\PrIC₃\text{max}(s₁ \models \emptyset^n B) > \lambda\). Furthermore, any sound implementation of Strengthen₄H (cf. Def.4) either immediately terminates \(\PrIC₃\)₄H by returning false or restores the \(\PrIC₃\) invariants for \(F₀, \ldots, F_k\). If the former case never arises, then Strengthen₄H will eventually restore the \(\PrIC₃\) invariants for a frame sequence of length \(k = n\). By Lem.7 we have \(Fₙ[s₁] \geq \PrIC₃\text{max}(s₁ \models \emptyset^n B) > \lambda\) contradicting frame-safety.

**PrIC₃₄H terminates for safe MDPs.** Standard IC3 terminates on safe finite TSs as there are only finitely many different frames, making every ascending chain of frames eventually stabilize. For us, frames map states to probabilities (Chall.1), yielding infinitely many possible frames even for finite MDPs. Hence, Strengthen₄H need not ever yield a stabilizing chain of frames. If it continuously fails to stabilize while repeatedly reasoning about the same set of states, we give up. \(\PrIC₃\)₄H checks this by comparing the subsystem Strengthen₄H operates on with the one it operated on in the previous loop iteration (l.8).

**Theorem 2.** If Strengthen₄H and Propagate terminate, then \(\PrIC₃\)₄H terminates.

**Recovery Statement 2.** For qual. reachability \((\lambda = 0)\), \(\PrIC₃\)₄H never terminates in l.8

**PrIC₃₄H is incomplete.** Standard IC3 either proves safety or returns false and a counterexample—a single path from the initial to a bad state. As single paths are insufficient as counterexamples in MDPs (Chall.2), \(\PrIC₃\)₄H instead returns a subsystem of the MDP \(\emptyset\) provided by Strengthen₄H. However, as argued above, we cannot trust
We denote such an obligation by \( F_i \). When the main loop of \( \PrIC_3 \) we set \( F_i \) to standard
ences to standard
IC3
which may spawn additional obligations that have to be resolved first to maintain relative
specification (Def. 4) and discuss its correctness.
the values assigned to state \( s \) (thus have to further decrease some entries in
\( F \) neither initiality nor the chain property (Defs. 3.1, 3.2). It may, however, violate relative
inductivity (Def. 3.4), i.e.,
\[ \triangle \]
chain for two thresholds:
\[ \PrIC_3 \] for every state, exactly one action is enabled, i.e., we consider a Markov chain. Fig. 2
depicts the frame sequences computed by \( \PrIC_3 \) (for a reasonable \( \mathcal{H} \)) on that Markov
chain for two thresholds: \( \frac{5}{9} = \PrIC_3^{\max} (s_0) = \emptyset B \) and \( \frac{9}{10} \). In particular, notice that proving
the coarser bound of \( \frac{9}{10} \) requires fewer frames than proving the exact bound of \( \frac{5}{9} \).

4 Strengthening in \( \PrIC_3 \)

When the main loop of \( \PrIC_3 \) has created a new frame \( F_k = 1 \) in its previous iteration, this
frame may violate frame-safety (Def. 3.3) because of \( F_k[s] = 1 \). The task of
\( \text{Strengthen}_{\mathcal{H}} \) is to restore the \( \PrIC_3 \) invariants on all frames \( F_0, \ldots, F_k \). To this end, our
first obligation is to lower the value in frame \( i = k \) for state \( s = s_f \) to \( \delta = \lambda \in [0, 1] \). We
denote such an obligation by \((i, s, \delta)\). Observe that implicitly \( \delta = 0 \) in the qualitative
case, i.e., when proving unreachability. An obligation \((i, s, \delta)\) is resolved by updating
the values assigned to state \( s \) in all frames \( F_0, \ldots, F_i \) to at most \( \delta \). That is, for all \( j \leq i \), we set \( F_j[s] \) to the minimum of \( \delta \) and the original value \( F_j[s] \). Such an update affects
neither initiality nor the chain property (Defs. 3.1, 3.2). It may, however, violate relative
inductivity (Def. 3.4), i.e., \( \Phi(F_{i-1}) \leq F_i \). Before resolving obligation \((i, s, \delta)\), we may
thus have to further decrease some entries in \( F_{i-1} \) as well. Hence, resolving obligations may spawn additional obligations which have to be resolved first to maintain relative
inductivity. In this section, we present a generic instance of \( \text{Strengthen}_{\mathcal{H}} \) meeting its
specification (Def. 4) and discuss its correctness.

\( \text{Strengthen}_{\mathcal{H}} \) by example. \( \text{Strengthen}_{\mathcal{H}} \) is given by the pseudo code in Alg. 2:

\[ \begin{align*}
\text{Strengthen}_{\mathcal{H}}(s, \delta) = & \text{false} \\
& \text{if } \text{the MDP is safe; otherwise, it returns false and provides a true counterexample witnessing that the MDP is unsafe.}
\end{align*} \]

Example 2. We conclude this section with two example executions of \( \PrIC_3 \) on a
simplified version of the MDP in Fig. 1. Assume that action \( b \) has been removed. Then,
for every state, exactly one action is enabled, i.e., we consider a Markov chain. Fig. 2
shows two runs of \( \PrIC_3 \) on the Markov chain induced by selecting action \( a \) in Fig. 1.
For every iteration, frames are recorded after invocation of \( \text{Strengthen}_{\mathcal{H}} \).

\( \text{Strengthen}_{\mathcal{H}} \) provides a stabilizing chain of frames. Reporting false thus only means
that the given MDP may be unsafe; the returned subsystem has to be analyzed further.

The full \( \PrIC_3 \) algorithm presented in Sect. 5 addresses this issue. Exploiting the
subsystem returned by \( \PrIC_3 \), \( \PrIC_3 \) returns true if the MDP is safe; otherwise, it
returns false and provides a true counterexample witnessing that the MDP is unsafe.

\( \Delta \)
why it is unable to do so. We first consider an execution where the latter does not arise:

Example 3. We zoom in on Ex. 2. Prior to the second iteration, we have created the following three frames assigning values to the states $s_0, s_5$:

$$F_0 = (0, 0, 0, 0, 1), \quad F_1 = (5/8, 1, 1, 1, 1), \quad \text{and} \quad F_2 = 1.$$

To keep track of unresolved obligations $(i, s, \delta)$, Strengthen$_{\mathcal{H}}$ employs a priority queue $Q$ which pops obligations with minimal frame index $i$ first. Our first step is to ensure frame-safety of $F_2$, i.e., alter $F_2$ so that $F_2[s_0] \leq 5/8$; we thus initialize the queue $Q$ with the initial obligation $(2, s_0, 5/8)$ (l. 1). To do so, we check whether updating $F_2[s_0]$ to $5/8$ would invalidate relative inductivity (l. 1). This is indeed the case:

$$\Phi(F_1)[s_0] = 1/2 \cdot F_1[s_1] + 1/2 \cdot F_1[s_2] = 1 \not\leq 5/8.$$  

To restore relative inductivity, Strengthen$_{\mathcal{H}}$ spawns one new obligation for each relevant successor of $s_0$. These have to be resolved before retrying to resolve the old obligation.\footnote{We assume that the set $\text{Succs}(s, a) = \{s' \in S \mid P(s, a, s') > 0\}$ of relevant $a$-successors of state $s$ is returned in some arbitrary, but fixed order.}

In contrast to standard IC3, spawning obligations involves finding suitable probabilities $\delta$ (l. 7). In our example this means we have to spawn two obligations $(1, s_1, \delta_1)$ and $(1, s_2, \delta_2)$ such that $1/2 \cdot \delta_1 + 1/2 \cdot \delta_2 \leq 5/8$. There are infinitely many choices for $\delta_1$ and $\delta_2$ satisfying this inequality. Assume some heuristic $\mathcal{H}$ chooses $\delta_1 = 11/18$ and $\delta_2 = 1/2$; we push obligations $(1, s_1, 11/18)$, $(1, s_2, 1/2)$, and $(2, s_0, 5/8)$ (l. 8). In the next iteration, we first pop obligation $(1, s_1, 11/18)$ (l. 3) and find that it can be resolved without violating relative inductivity (l. 6). Hence, we set $F_1[s_1]$ to $11/18$ (l. 11); no new obligation is spawned. Obligation $(1, s_2, 1/2)$ is resolved analogously; the updated frame is
We discuss three possible approaches to generalization in Sect. 6.2. We remark that, analogously to standard (l. 6), we first need to update the values of the successor states single successor state be resolved first (ll. 7–9). It is noteworthy that, for a TS, a single action leads to a single action frame required for pushing obligations (l. 7). Assume for an obligation (that resolving an obligation in l. 9. Let us thus look closer at how obligations are spawned: Whenever we detect generalization accompanied by Strengthen only scenario in which Strengthen Theorem 3. Procedure Procedure Q l. 9, the size of Lemma 4. Procedure Procedure Q l. 9, the size of s is added to δ, i.e.,

$$F \langle s \mapsto \delta \rangle [s'] = \begin{cases} \delta, & \text{if } s' = s, \\ F[s'], & \text{otherwise.} \end{cases}$$

Indeed, resolving obligation (i, s, δ) in l. 11 lowers the values assigned to state s to at most δ without invalidating the PrIC3 invariants:

**Lemma 3.** Let (i, s, δ) be an obligation and F₀, . . . , Fᵢ and Fᵢ₊₁ be frames with \( \Phi(Fᵢ₊₁)[s] \leq \delta \). Then PrIC3Inv(F₀, . . . , Fᵢ) implies

$$\PrIC3Inv \left( F₀ \langle s \mapsto \min (F₀[s], \delta) \rangle, . . . , Fᵢ \langle s \mapsto \min (Fᵢ[s], \delta) \rangle \right).$$

Crucially, the precondition of Def. 4 guarantees that all PrIC3 invariants except frame safety hold initially. Since these invariants are never invalidated due to Lem. 3, Alg. 2 is a sound implementation of Strengthenyun.2 if it restores frame safety whenever it returns true, i.e., once it leaves the loop with an empty obligation queue Q (ll. 12–13). Now, an obligation (i, s, δ) is only popped from Q in l. 9 as (i, s, δ) is added to Q upon reaching l. 9 the size of Q can only ever be reduced (without returning false) by resolving (i, s, δ) in l. 11. Hence, Alg. 2 does not return true unless it restored frame safety by resolving, amongst all other obligations, the initial obligation (k, s₁, λ). Consequently:

**Lemma 4.** Procedure Strengthenyun.2 is sound, i.e., it satisfies the specification in Def. 4

**Theorem 3.** Procedure PrIC3yun.2 is sound, i.e., satisfies the specification in Thm. 1

We remark that, analogously to standard IC3, resolving an obligation in l. 11 may be accompanied by generalization. That is, we attempt to update the values of multiple states at once. Generalization is, however, highly non-trivial in a probabilistic setting. We discuss three possible approaches to generalization in Sect. 6.2.

**Strengthenyun.2 terminates.** We now show that Strengthenyun.2 as in Alg. 2 terminates. The only scenario in which Strengthenyun.2 may not terminate is if it keeps spawning obligations in l. 9. Let us thus look closer at how obligations are spawned: Whenever we detect that resolving an obligation (i, s, δ) would violate relative inductivity for some action \( a \) (l. 6), we first need to update the values of the successor states \( s₁, \ldots, sₙ \in \text{Succ}(s, a) \) in frame i−1, i.e., we push the obligations \( (i−1, s₁, δ₁), \ldots, (i−1, sₙ, δₙ) \) which have to be resolved first (ll. 7–9). It is noteworthy that, for a TS, a single action leads to a single successor state \( s₁ \). Alg. 2 employs a heuristic \( \mathcal{H} \) to determine the probabilities required for pushing obligations (l. 7). Assume for an obligation (i, s, δ) that the check
in l. 6 yields \( \exists a \in \text{Act}(s) : \Phi_a(F_{i-1})[s] > \delta \). Then \( H \) takes \( s, a, \delta \) and reports some probability \( \delta_j \) for every \( a \)-successor \( s_j \) of \( s \). However, an arbitrary heuristic of type \( H : S \times \text{Act} \times [0,1] \rightarrow [0,1]^* \) may lead to non-terminating behavior: If \( \delta_1, \ldots, \delta_n = F_{i-1}[s_1] \ldots F_{i-1}[s_n] \), then the heuristic has no effect. It is thus natural to require that an adequate heuristic \( H \) yields probabilities such that the check \( \Phi_a(F_{i-1})[s] > \delta \) in l. 6 cannot succeed twice for the same obligation \((i, s, \delta)\) and same action \( a \). Formally, this is guaranteed by the following:

**Definition 5.** Heuristic \( H \) is adequate if the following triple is valid (for any frame \( F \)):

\[
\begin{align*}
\{ & \text{Succ}(s, a) = s_1, \ldots, s_n \} \\
\delta_1, \ldots, \delta_n & \leftarrow H(s, a, \delta) \\
\{ & \Phi_a(F(s_1 \mapsto \delta_1) \ldots (s_n \mapsto \delta_n))[s] \leq \delta \} \quad \triangle
\end{align*}
\]

Details regarding our implementation of heuristic \( H \) are found in Section 6.1.

For an adequate heuristic, attempting to resolve an obligation \((i, s, \delta)\) (ll. 3 – 11) either succeeds after spawning it at most \(|\text{Act}(s)|\) times or \(\text{Strengthen}_H\) returns \text{false}. By a similar argument, attempting to resolve an obligation \((i > 0, s, \____)\) leads to at most \(\sum_{a \in \text{Act}(s)} |s' \in S \mid P(s, a, s') > 0|\) other obligations of the form \((i-1, s', \____)\). Consequently, the total number of obligations spawned by Alg. 2 is bounded. Since Alg. 2 terminates if all obligations have been resolved (l. 12) and each of its loop iterations either returns \text{false}, spawns obligations, or resolves an obligation, we conclude:

**Lemma 5.** \(\text{Strengthen}_H(F_0, \ldots, F_k)\) terminates for every adequate heuristic \( H \).

**Recovery Statement 3.** Let \( H \) be adequate. Then for qualitative reachability (\( \lambda = 0 \)), all obligations spawned by \(\text{Strengthen}_H\) as in Alg. 2 are of the form \((i, s, 0)\).

**Strengthen\_H returns false.** There are two cases in which \(\text{Strengthen}_H\) fails to restore the \text{PrIC3} invariants and returns \text{false}. The first case (the left disjunct of l. 3) is that we encounter an obligation for frame \( F_0 \). Resolving such an obligation would inevitably violate \text{initiality}; analogously to standard \text{IC3}, we thus return \text{false}.

The second case (the right disjunct of l. 3) is that we encounter an obligation \((i, s, \delta)\) for a bad state \( s \in B \) with a probability \( \delta < 1 \) (though, obviously, all \( s \in B \) have probability \( = 1 \)). Resolving such an obligation would inevitably prevents us from restoring \text{relative inductivity}: If we updated \( F_i[s] \) to \( \delta \), we would have \( \Phi(F_{i-1})[s] = 1 > \delta = F_i[s] \). Notice that, in contrast to standard \text{IC3}, this second case can occur in \text{PrIC3}:

**Example 4.** Assume we have to resolve an obligation \((i, s_3, \frac{1}{2})\) for the MDP in Fig. 1. This involves spawning obligations \((i-1, s_4, \delta_1)\) and \((i-1, s_5, \delta_2)\), where \( s_3 \) is a bad state, such that \( \frac{1}{2} \cdot \delta_1 + \frac{1}{2} \cdot \delta_2 \leq \frac{1}{2} \). Even for \( \delta_1 = 0 \), this is only possible if \( \delta_2 \leq \frac{1}{4} < 1 \). \triangle

**Strengthen\_H cannot prove unsafety.** If standard \text{IC3} returns \text{false}, it proves unsafety by constructing a counterexample, i.e., a \text{single path from the initial state to a bad state}. If \text{PrIC3} returns \text{false}, there are two possible reasons: Either the MDP is indeed unsafe, or the heuristic \( H \) at some point selected probabilities in a way such that \(\text{Strengthen}_H\) is unable to restore the \text{PrIC3} invariants (even though the MDP might in fact be safe).
Data: global MDP $M$, set of bad states $B$, threshold $\lambda$
Result: $\text{true}$ iff $\Pr_{\text{max}}(s_I \models \diamond B) \leq \lambda$

1. $\Omega \leftarrow \text{Initialize}();$ $\text{touched} \leftarrow \{s_I\};$
2. do
3. \quad $\mathcal{H} \leftarrow \text{CreateHeuristic}(\Omega);$ $\text{safe, subsystem} \leftarrow \text{PrlC3}_H() ;$
4. \quad if $\text{safe}$ then return $\text{true};$
5. \quad if $\text{CheckRefutation}(\text{subsystem})$ then return $\text{false};$
6. \quad $\text{touched} \leftarrow \text{Enlarge}(\text{touched, subsystem});$
7. \quad $\Omega \leftarrow \text{Refine}(\Omega, \text{touched});$
8. while $\text{touched} \neq S;$
9. return $\Omega(s_I) \leq \lambda$

**Algorithm 3: PrlC3:** The outermost loop dealing with possibly imprecise heuristics

Strengthen$_{H}$ thus only returns a potential counterexample which either proves unsafety or indicates that our heuristic was inappropriate.

Counterexamples in our case consist of subsystems rather than a single path (see Chall. 2 and Sec. 5). Strengthen$_{H}$ hence returns the set $Q.\text{touched}()$ of all states that eventually appeared in the obligation queue. This set is a conservative approximation, and optimizations as in $11$ may be beneficial. Furthermore, in the qualitative case, our potential counterexample subsumes the counterexamples constructed by standard IC3:

**Recovery Statement 4.** Let $H_0$ be the adequate heuristic mapping every state to $0$. For qual. reachability ($\lambda = 0$), if success = false is returned by Strengthen$_{H_0}(F_0, \ldots, F_k)$, then $Q.\text{touched}()$ contains a path from the initial to a bad state.$^{10}$

## 5 Dealing with Potential Counterexamples

Recall that our core algorithm PrlC3$_H$ is incomplete for a fixed heuristic $\mathcal{H}$: It cannot give a conclusive answer whenever it finds a potential counterexample for two possible reasons: Either the heuristic $\mathcal{H}$ turned out to be inappropriate or the MDP is indeed unsafe. The idea to overcome the former is to call PrlC3$_H$ finitely often in an outer loop that generates new heuristics until we find an appropriate one: If PrlC3$_H$ still does not report safety of the MDP, then it is indeed unsafe. We do not blindly generate new heuristics, but use the potential counterexamples returned by PrlC3$_H$ to refine the previous one.

Let consider the procedure PrlC3 in Alg. 3 which wraps our core algorithm PrlC3$_H$ in more detail: First, we create an oracle $\Omega: S \rightarrow [0, 1]$ which (roughly) estimates the probability of reaching $B$ for every state. A perfect oracle would yield precise maximal reachability probabilities, i.e., $\Omega(s) = \Pr_{\text{max}}(s \models \diamond B)$ for every state $s$. We construct oracles by user-supplied methods (highlighted in blue). Examples of implementations of all user-supplied methods in Alg. 3 are discussed in Sect. 7.

Assuming the oracle is good, but not perfect, we construct an adequate heuristic $\mathcal{H}$ selecting probabilities based on the oracle$^{11}$ for all successors of a given state: There

---

$^{10}$ $Q.\text{touched}()$ might be restricted to only contain this path by some simple adaptations.

$^{11}$ We thus assume that heuristic $\mathcal{H}$ invokes the oracle whenever it needs to guess some probability.
are various options. The simplest is to pass-through the oracle values. A version that is more robust against noise in the oracle is discussed in Sect. [ ] We then invoke PrIC3_H. If PrIC3_H reports safety, the MDP is indeed safe by the soundness of PrIC3_H.  

**Check refutation.** If PrIC3_H does not report safety, it reports a subsystem that hints to a potential counterexample. Formally, this subsystem is a subMDP of states that were ‘visited’ during the invocation of Strengthen_H.  

**Definition 6 (subMDP).** Let $M = (S, s_I, Act, P)$ be an MDP and let $S' \subseteq S$ with $s_I \in S'$. We call $M_{S'} = (S', s_I, Act, P')$ the subMDP induced by $M$ and $S'$, where for all $s, s' \in S'$ and all $a \in Act$, we have $P'(s, a, s') = P(s, a, s')$. △  

A subMDP $M_{S'}$ may be substochastic where missing probability mass never reaches a bad state. Def. [1] is thus relaxed: For all states $s \in S'$ we require that $\sum_{s' \in S'} P(s, a, s') \leq 1$. If the subsystem is unsafe, we can conclude that the original MDP $M$ is also safe.  

**Lemma 6.** If $M'$ is a subMDP of $M$ and $M'$ is unsafe, then $M$ is also unsafe.  

The role of CheckRefutation is to establish whether the subsystem is indeed a true counterexample or a spurious one. Formally, CheckRefutation should ensure:  

{ true } $res \leftarrow$ CheckRefutation(subsystem) { $res = \text{true} \iff M_{subsystem} \text{ unsafe}$ }.  

Again, PrIC3 is backward compatible in the sense that a single fixed heuristic is always sufficient when reasoning about reachability ($\lambda = 0$).  

**Recovery Statement 5.** For qualitative reachability ($\lambda = 0$) and the heuristic $H_0$ from Recovery Statement [ ] PrIC3 invokes its core PrIC3_H exactly once.  

This statement is true, as PrIC3_H returns either safe or a subsystem containing a path from the initial state to a bad state. In the latter case, CheckRefutation detects that the subsystem is indeed a counterexample which cannot be spurious in the qualitative setting.  

We remark that the procedure CheckRefutation invoked in l. 5 is a classical fallback; it runs an (alternative) model checking algorithm, e.g., solving the set of Bellman equations, for the subsystem. In the worst case, i.e., for $S' = S$, we thus solve exactly our problem statement. Empirically (Tab. 1) we observe that for reasonable oracles the procedure CheckRefutation is invoked on significantly smaller subMDPs. However, in the worst case the subMDP must include all paths of the original MDP, and then thus coincides.  

**Refine oracle.** Whenever we have neither proven the MDP safe nor unsafe, we refine the oracle to prevent generating the same subsystem in the next invocation of PrIC3_H. To ensure termination, oracles should only be refined finitely often. That is, we need some progress measure. The set touched overapproximates all counterexamples encountered in some invocation of PrIC3_H and we propose to use its size as the progress measure. While there are several possibilities to update touched through the user-defined procedure Enlarge (l. 6), every implementation should hence satisfy { true } $touched' \leftarrow$ Enlarge($touched$, __) { $|touched'| > |touched|$ }. Consequently, after finitely many iterations, the oracle is refined with respect to all states. In this case, we may as well rely on solving the characteristic LP problem:
module ex
  c : [0..20] init 0; f : [0..1] init 0;
  [] c<20 -> 0.1:(f'=1) + 0.9:(c'=c+1); // cmd 1
  [] c<10 -> 0.2:(f'=1) + 0.8:(c'=c+2);
endmodule

(a) Prism code snippet

(b) Part of the corresponding MDP

Fig. 3. Illustrative Prism-style probabilistic guarded command language example

Lemma 7. The algorithm PrIC3 in Alg. 2 is sound and complete if Refine(\Omega, S) returns a perfect oracle \Omega (with S is the set of all states).

Weak assumptions on Refine are possible, but are beyond the scope of this paper. Moreover, the above lemma does not rely on the abstract concept that heuristic \mathcal{H} provides suitable probabilities after finitely many refinements.\footnote{One could of course now also create a heuristic that is trivial for a perfect oracle and invoke PrIC3_\mathcal{H} with the heuristic for the perfect oracle, but there really is no benefit in doing so.}

6 Practical PrIC3

So far, we gave a conceptual view on PrIC3, but now take a more practical stance. We detail important features of effective implementations of PrIC3 (based on our empirical evaluation). We first describe an implementation without generalization, and then provide a prototypical extension that allows for three variants of generalization.

6.1 A Concrete PrIC3 Instance without Generalization

Input. We describe MDPs using the Prism guarded command language\footnote{Preprocessing ensures a single thread (module) and no deadlocks.}, exemplified in Fig. 3. States are described by valuations to \( m \) (integer-valued) program variables vars, and outgoing actions are described by commands of the form

\[
[] \text{guard} \rightarrow \text{prob}_1 : \text{update}_1 & \ldots & \text{prob}_k : \text{update}_k
\]

If a state satisfies \text{guard}, then the corresponding action with \( k \) branches exists; probabilities are given by \text{prob}_i, the successor states are described by \text{update}_i, see Fig. 3b

Encoding. We encode frames as logical formulae. Updating frames then corresponds to adding conjuncts, and checking for relative inductivity is a satisfiability call. Our encoding is as follows: States are assignments to the program variables, i.e., \text{States} = \mathbb{Z}^m. We use various uninterpreted functions, to whom we give semantics using appropriate constraints. Frame\footnote{In each operation, we only consider a single frame.} are represented by uninterpreted functions \text{Frame} : \text{States} \rightarrow \mathbb{R} satisfying \text{Frame}(s) = d \text{ implies } F[s] \geq d. Likewise, the Bellman operator is an uninterpreted function \text{Phi} : \text{States} \rightarrow \mathbb{R} such that \text{Phi}(s) = d \text{ implies } \Phi(F)[s] \geq d.

Finally, we use \text{Bad} : \text{States} \rightarrow \mathbb{B} with \text{Bad}(s) \text{ iff } s \in B.
Among the appropriate constraints, we ensure that variables are within their range, bound the values for the frames, and enforce $\Phi(s) = 1$ for $s \in B$. We encode the guarded commands as exemplified by this encoding of the first command in Fig. 5:

\begin{align*}
\forall s \in \text{States}: & \neg \text{Bad}(s) \land s[c] < 20 \\
\implies & \Phi(s) = 0.1 \cdot \text{Frame}((s[c], 1)) + 0.9 \cdot \text{Frame}((s[c] + 1, s[f])).
\end{align*}

In our implementation, we optimize the encoding. We avoid the uninterpreted functions by applying an adapted Ackerman reduction. We avoid universal quantifiers, by first observing that we always ask whether a single state is not inductive, and then unfolding the guarded commands in the constraints that describe a frame. That encoding grows linear in the size of the maximal out-degree of the MDP, and is in the quantifier-free fragment of linear arithmetic (QFLRIA).

**Heuristic.** We select probabilities $\delta_i$ by solving the following optimization problem, with variables $x_i$, $\text{range}(x_i) \in [0, 1]$, for states $s_i \in \text{Succs}(s, a)$ and oracle $\Omega$:

\[
\text{minimize} \sum_{s_i \in B} \frac{x_i - \Omega(x_i)}{\sum_{j=1}^k x_j} \text{ s.t. } \delta = \sum_{i=1}^k P(s, a, s_i) \cdot \begin{cases} 
1, & \text{if } s_i \in B, \\
x_i, & \text{else}.
\end{cases}
\]

The constraint ensures that, if the values $x_i$ correspond to the actual reachability probabilities from $s_i$, then the reachability from state $s$ is exactly $\delta$. A constraint stating that $\delta \geq \ldots$ would also be sound, but we choose equality as it preserves room between the actual probability and the threshold we want to show. Finally, the objective function aims to preserve the ratio between the suggested probabilities.

**Repushing and breaking cycles.** Repushing is an essential ingredient of both standard IC3 and PrI3C. Intuitively, we avoid opening new frames and spawning obligations that can be deduced from current information. Since repushing generates further obligations in the current frame, its implementation requires that the detection of Zeno-behavior has to be moved from PrI3C$_H$ into the Strengthen$_H$ procedure. Therefore, we track the histories of the obligations in the queue. Furthermore, once we detect a cycle we first try to adapt the heuristic $H$ locally to overcome this cyclic behavior instead of immediately giving up. This local adaption reduces the number of PrI3C$_H$ invocations.

**Extended queue.** In contrast to standard IC3, the obligation queue might contain entries that vary only in their $\delta$ entry. In particular, if the MDP is not a tree, it may occur that the queue contains both $(i, s, \delta)$ and $(i, s, \delta')$ with $\delta > \delta'$. Then, $(i, s, \delta')$ can be safely pruned from the queue. Similarly, after handling $(i, s, \delta)$, if some fresh obligation $(i, s, \delta'' > \delta)$ is pushed to the queue, it can be substituted with $(i, s, \delta)$. To efficiently operationalize these observations, we keep an additional mapping which remains intact over multiple invocations of Strengthen$_H$. We furthermore employed some optimizations for $Q$.touched() aiming to track potential counterexamples better. After refining the heuristic, one may want to reuse frames or the obligation queue, but empirically this leads to performance degradation as the values in the frames are inconsistent with behavior suggested by the heuristic.

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15 If $\max \Omega(s_j) = 0$, we assume $\forall j. \Omega(s_j) = 0.5$. If $\delta = 0$, we omit rescaling to allow $\sum x_j = 0$. 
6.2 Concrete PrI\textsc{C3} with Generalization

So far, frames are updated by changing single entries whenever we resolve obligations \((i, s, \delta)\), i.e., we add conjunctions of the form \(F_i[s] \leq \delta\). Equivalently, we may add a constraint \(\forall s' \in S : F_i[s'] \leq p_{\{s\}}(s')\) with \(p_{\{s\}}(s) = \delta\) and \(p_{\{s\}} = 1\) for all \(s' \neq s\).

Generalization in IC\textsc{3} aims to update a set \(G\) (including \(s\)) of states in a frame rather than a single one without invalidating relative inductivity. In our setting, we thus consider a function \(p_G : G \to [0, 1]\) with \(p_G(s) \leq \delta\) that assigns (possibly different) probabilities to all states in \(G\). Updating a frame then amounts to adding the constraint

\[
\forall s \in \text{States}: s \in G \implies \text{Frame}(s) \leq p_G(s).
\]

Standard IC\textsc{3} generalizes by iteratively “dropping” a variable, say \(v\). The set \(G\) then consists of all states that do not differ from the fixed state \(s\) except for the value of \(v\).\(^{15}\) We take the same approach by iteratively dropping program variables. Hence, \(p_G\) effectively becomes a mapping from the value \(s[v]\) to a probability. We experimented with four types of functions \(p_G\) that we describe for Markov chains. The ideas are briefly outlined below; details are beyond the scope of this paper.

\textbf{Constant} \(p_G\). Setting all \(s \in G\) to \(\delta\) is straightforward but empirically not helpful.

\textbf{Linear interpolation}. We use a linear function \(p_G\) that interpolates two points. The first point \((s[v], \delta)\) is obtained from the obligation \((i, s, \delta)\). For a second point, consider the following: Let Com be the unique \(^{16}\) command active at state \(s\). Among all states in \(G\) that are enabled in the guard of Com, we take the state \(s'\) in which \(s'[v]\) is maximal\(^{18}\). The second point for interpolation is then \((s'[v], \Phi(F_{i-1})[s'])\). If the relative inductivity fails for \(p_G\) we do not generalize with \(p_G\), but may attempt to find other functions.

\textbf{Polynomial interpolation}. Rather than linearly interpolating between two points, we may interpolate using more than two points. In order to properly fit these points, we can use a higher-degree polynomial. We select these points using counterexamples to generalization (CTGs): We start as above with linear interpolation. However, if \(p_G\) is not relative inductive, the SMT solver yields a model with state \(s''\in G\) and probability \(\delta''\), with \(s''\) violating relative inductivity, i.e., \(\Phi(F_{i-1})[s''] > \delta''\). We call \((s'', \Phi(F_{i-1})[s''])\) a CTG, and \((s''[v], \Phi(F_{i-1})[s''])\) is then a further interpolation point, and we repeat.

Technically, when generalizing using nonlinear constraints, we use real-valued arithmetic with a branch-and-bound-style approach to ensure integer values.

\textbf{Hybrid interpolation}. In polynomial interpolation, we generate high-degree polynomials and add them to the encoding of the frame. In subsequent invocations, reasoning efficiency is drastically harmed by these high-degree polynomials. Instead, we soundly approximate \(p_G\) by a piecewise linear function, and use these constraints in the frame.

\(^{15}\) Formally, \(G = \{s' \mid \text{for all } v' \in \text{vars} \setminus \{v\} : s'(v') = s(v')\}\).

\(^{16}\) Recall that we have a Markov chain consisting of a single module

\(^{16}\) This implicitly assumes that \(v\) is increased. Adaptations are possible.
7 Experiments

We assess how PrIC3 may contribute to the state of the art in probabilistic model checking. We do some early empirical evaluation showing that PrIC3 is feasible. We see ample room for further improvements of the prototype.

Implementation. We implemented a prototype\(^{19}\) of PrIC3 based on Sect. 6.1 in Python. The input is represented using efficient data structures provided by the model checker Storm. We use an incremental instance of Z3\(^{16}\) for each frame, as suggested in [22]. A solver for each frame is important to reduce the time spent on pushing the large frame-encodings. The optimization problem in the heuristic is also solved using Z3. All previously discussed generalizations (none, linear, polynomial, hybrid) are supported.

Oracle and refinement. We support the (pre)computation of four different types of oracles for the initialization step in Alg. 5: (1) A perfect oracle solving exactly the Bellman equations. Such an oracle is unrealistic, but interesting from a conceptual point. (2) Relative frequencies by recording all visited states during simulation. This idea is a naïve simplification of Q-learning. (3) Model checking with decision diagrams (DDs) and few value iterations. Often, a DD representation of a model can be computed fast, and the challenge is in executing sufficient value iterations. We investigate whether doing few value iterations yields a valuable oracle (and covers states close to bad states). (4) Solving a (pessimistic) LP from BFS partial exploration. States that are not expanded are assumed bad. Roughly, this yields oracles covering states close to the initial states.

To implement Refine (cf. Alg. 1, 7), we create an LP for the subMDP induced by the touched states. For states whose successors are not in the touched states, we add a transition to B labeled with the oracle value as probability. The solution of the resulting LP updates the entries corresponding to the touched states.

For Enlarge (cf. Alg. 1, 6), we take the union of the subsystem and the touched states. If this does not change the set of touched states, we also add its successors.

Setup. We evaluate the run time and memory consumption of our prototype of PrIC3. We choose a combination of models from the literature (BRP\(^{20}\), ZeroConf\(^{17}\)) and some structurally straightforward variants of grids (chain, double chain; see App. A). Since our prototype lacks the sophisticated preprocessing applied by many state-of-the-art model checkers, it is more sensitive to the precise encoding of a model, e.g., the number of commands. To account for this, we generated new encodings for all models. All experiments were conducted on an single core of an Intel® Xeon® Platinum 8160 processor. We use a 15 minute time-limit and report TO otherwise. Memory is limited to 8GB; we report MO if it is exceeded. Apart from the oracle, all parameters of our prototype remain fixed over all experiments. To give an impression of the run times, we compare our prototype with both the explicit (Storm\(_{\text{sparse}}\)) and DD-based (Storm\(_{\text{dd}}\)) engine of the model checker Storm 1.4, which compared favourably in QComp\(^{28}\).

Results. In Tab. 1 we present the run times for various invocations of our prototype and Oracle\(^{20}\). In particular, we give the model name and the number of (non-trivial) states in the particular instance, and the (estimated) actual probability to reach B. For

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\(^{19}\) The prototype is available open-source from [https://github.com/moves-rwth/PrIC3](https://github.com/moves-rwth/PrIC3).

\(^{20}\) We explore min\(|S|, 5000\) states using BFS and Storm.
Table 1. Empirical results. Run times are in seconds; time out = 15 minutes.

| $|S|$ | $\Pr_{\text{max}} (s_f \models \phi_B)$ | $J$ | min | $\text{lin}$ | $\text{pol}$ | $\text{hyb}$ | $\text{Storm}_{\text{safe}}$ | $\text{Storm}_{\text{fail}}$ |
|---|---|---|---|---|---|---|---|---|
| PRP | $10^3$ | $0.035$ | $0.01$ | $51.3$ | $324$ | $125.8$ | $324$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{MO}$ | $\text{MO}$ | $<0.1$ | $0.12$ |
| | $10^6$ | $0.005$ | $10.9$ | $188$ | $38.3$ | $188$ | $\text{TO}$ | $\text{MO}$ | $\text{MO}$ | $<0.1$ | $0.1$ |
| ZeroConf | $10^3$ | $0.9$ | $0.52$ | $0.45$ | $0.9$ | $0$ | $0.1$ | $0$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $296.8$ |
| | $10^6$ | $0.5$ | $0.45$ | $<0.1$ | $0.9$ | $0$ | $0$ | $0$ | $\text{MO}$ | $\text{TO}$ | $\text{MO}$ | $\text{MO}$ | $\text{MO}$ | $<0.1$ | $282.6$ |
| | $10^9$ | $-0.55$ | $0.75$ | $0.52$ | $0.45$ | $<0.1$ | $0$ | $0$ | $\text{MO}$ | $\text{MO}$ | $\text{MO}$ | $\text{MO}$ | $\text{MO}$ | $<0.1$ | $300.2$ |
| Chain | $10^3$ | $0.394$ | $0.35$ | $10.18$ | $431$ | $119.5$ | $431$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $0.1$ |
| | $10^6$ | $0.3$ | $46.1$ | $357$ | $64.0$ | $357$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $0$ |
| Double Chain | $10^3$ | $0.394$ | $0.394$ | $0.9$ | $0.4$ | $0.9$ | $0$ | $0$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $4.5$ |
| | $10^6$ | $0.3$ | $0.3$ | $0$ | $0$ | $0$ | $0$ | $0$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $4.9$ |
| | $10^{12}$ | $0.394$ | $0.4$ | $0.4$ | $0$ | $0$ | $0$ | $0$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $\text{TO}$ | $<0.1$ | $0.1$ |

Each model, we consider multiple thresholds $\lambda$. The next 8 columns report on the four variants of PrIC3 with varying generalization schemes. Besides the scheme with the run times, we report for each scheme the number of states of the largest (last) subsystem that CheckRefutation in Alg. 3, l. 5 was invoked upon (column $\text{sub}$). The last two columns report on the run times for Storm that we provide for comparison. In each row, we mark with purple MDPS that are unsafe, i.e., PrIC3 refutes these MDPS for the given threshold $\lambda$. We highlight the best configurations of PrIC3.

**Discussion.** Our experiments give a mixed picture on the performance of our implementation of PrIC3. On the one hand, Storm significantly outperforms PrIC3 on most models. On the other hand, PrIC3 is capable of reasoning about huge, yet simple, models with up to $10^{12}$ states that Storm is unable to analyze within the time and memory limits. There is more empirical evidence that PrIC3 may complement the state-of-the-art:

First, *the size of thresholds matters*. Our benchmarks show that—at least without generalization—more “wiggle room” between the precise maximal reachability probability and the threshold generally leads to a better performance. PrIC3 may thus prove bounds for large models where a precise quantitative reachability analysis is out of scope.

Second, PrIC3 *enjoys the benefits of bounded model checking*. In some cases, e.g., ZeroConf for $\lambda = 0.45$, PrIC3 refutes very fast as it does not need to build the whole model.

Third, if PrIC3 proves the safety of the system, it does so without relying on checking large subsystems in the CheckRefutation step.

Fourth, *generalization is crucial*. Without generalization, PrIC3 is unable to prove safety for any of the considered models with more than $10^3$ states. With generalization,
however, it can prove safety for very large systems and thresholds close to the exact reachability probability. For example, it proved safety of the Chain benchmark with $10^{12}$ states for a threshold of 0.4 which differs from the exact reachability probability by 0.006.

Fifth, there is no best generalization. There is no clear winner out of the considered generalization approaches. Linear generalization always performs worse than the others. In fact, it performs worse than no generalization at all. The hybrid approach, however, occasionally has the edge over the polynomial approach. This indicates that more research is required to find suitable generalizations.

In Appendix A, we also compare the additional three types of oracles (1–3). We observed that only few oracle refinements are needed to prove safety; for small models at most one refinement was sufficient. However, this does not hold if the given MDP is unsafe. DoubleChain with $\lambda = 0.15$, for example, and Oracle 2 requires 25 refinements.

8 Conclusion

We have presented PrIC3—the first truly probabilistic, yet conservative, extension of IC3 to quantitative reachability in MDPs. Our theoretical development is accompanied by a prototypical implementation and experiments. We believe there is ample space for improvements including an in-depth investigation of suitable oracles and generalizations.

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A  Further details for the experiments

\begin{verbatim}
module chain
  c : [0..N] init 0; f : [0..1] init 0;
  [1] c<>N -> p:(c'=c+1) + (1-p):(f'=1);
endmodule

module double_chain
  c : [0..N] init 0; f : [0..1] init 0; g : [0..1] init 0;
  [1] c<>N & g=0 -> p1:(c'=c+1) + p2:(g'=1) + p3 : (f'=1);
  [1] c<>N & g=1 -> q:(c'=c+1) + (1-q): (f'=1);
endmodule

label bad = f'=1

Fig. 4. Prism code for examples Chain and Double Chain
\end{verbatim}

In Fig. 4, we depict the precise encoding of the two variants of chains. For Table 2 (alternative oracles), we use only the smallest models from Table 1 as we focus on the effect of the oracles. The model name and the threshold \( \lambda \) thus identify the instance; \( \Omega \) refers to the oracle type. We then list the generalization approach. For each configuration, we report the number of iterations of PrIC3\( \mathcal{H} \) and the run time in seconds.

Table 3 provides additional empirical results for the benchmarks from Table 1: The number of calls to CheckRefutation and the percentage of the total runtime required by CheckRefutation.

B  Omitted Proofs

B.1  Proof of Theorem 1

Proof. We show that

\[ I = \text{PrIC3Inv}(F_0, \ldots, F_{k-1}) \land F_{k-1} \leq F_k \land \Phi(F_{k-1}) \leq F_k \]

is an invariant of the loop in PrIC3\( \mathcal{H} \).

Initialization. At the beginning of the loop, we have \( k = 1 \), \( F_0 = \Phi(0) \), and \( F_1 = \mathbf{1} \). PrIC3Inv(\( F_0 \)) holds trivially. Furthermore, we have \( F \leq \mathbf{1} \) for every frame \( F \in [0,1]^5 \), which gives us \( F_0 \leq F_1 \) and \( \Phi(F_0) \leq F_1 \).

\[ \neq \]

Consecution. Assume the loop invariant \( I \) holds at the beginning of some iteration. PrIC3\( \mathcal{H} \) immediately invokes Strengthen\( \mathcal{H} \) in line 4. If Strengthen\( \mathcal{H} \) returns success = false, we have nothing to show. Otherwise, i.e., if Strengthen\( \mathcal{H} \) returns success = true,

\[ 21 \] We use 100 value iteration steps for Oracle 3.
Table 2. Comparison of the number iterations of PrIC3’s outermost loop and its run times (in seconds) for three different oracles Ω.

| λ | Ω  | w/o lin pol | hyb  |
|---|---|---|---|
| 0.75 | 2 | TO | TO | TO | MO |
| 0.52 | 2 | TO | TO | 0 | 0.1 | 0.1 | 0.2 |
| 0.45 | 2 | TO | TO | 0.1 | 0.1 | 0.1 | 0.1 |
| 0.35 | 2 | TO | TO | 1 | 0.1 | 0.1 | 0.1 |
| 0.26 | 2 | TO | TO | 20 | 1.2 | 1.2 | 0.2 |
| 0.15 | 2 | TO | TO | 19 | 1.2 | 1.2 | 0.2 |
| 0.45 | 2 | TO | TO | 19 | 1.2 | 1.2 | 0.2 |
| 0.35 | 2 | TO | TO | 19 | 1.2 | 1.2 | 0.2 |
| 0.26 | 2 | TO | TO | 19 | 1.2 | 1.2 | 0.2 |
| 0.15 | 2 | TO | TO | 19 | 1.2 | 1.2 | 0.2 |

the specification of StrengthenH (Def. 4) implies that PrIC3Inv(F0, . . . , Fk) holds. Now observe that after line 5, we have Fk ≤ Fk+1 and Φ(Fk) ≤ Fk+1 since Fk+1 = 1. Since Propagate does not affect the PrIC3 invariants, these facts continue to hold after line 7.

If there is an 1 ≤ i ≤ k with Fk = Fk+1, Lemma 2 applies and we have Prmax(sI | = ♦B) ≤ λ, which is what we have to show.

To conclude our proof that I is a loop invariant, observe that after the assignment k ← k + 1 in line 9, we have

PrIC3Inv(F0, . . . , Fk−1) ∧ Fk−1 ≤ Fk ∧ Φ(Fk−1) ≤ Fk,

so I continues to hold at the end of that iteration.

B.2 Proof of Lemma 3

Proof. Let

F0′ = F0 ⟨s → min(F0[s], δ)⟩, . . . , Fk′ = Fk ⟨s → min(Fk[s], δ)⟩.

We consider each invariant separately.

Initiality. Since F0′ = F0, initiality is preserved.

Chain-Property. Assume F0′, . . . , Fk′ do not satisfy the chain-property. Then there is
Table 3. Additional empirical results. \#cr is the number of calls to CheckRefutation. crTime (%) is the percentage of the total runtime required by CheckRefutation.

| $|S|$ | $Pr_{max_k} (x_t = \emptyset R)$ | $t$ | $\lambda$ | $\Phi$ w/o lin pol hyb | $\Phi$ lin | $\Phi$ pol | $\Phi$ hyb | $\Phi$ crTime (%) |
|-----|-------------------|-----|-----------|-------------------|----------|----------|----------|------------------|
| $10^3$ | 0.035 | 0.01 | 43 | 45.4 | 43 | 17.0 | - | - | - | - |
| $10^4$ | 0.5 | 0.52 | 0.45 | 1 | 26.5 | 1 | 26.5 | 1 | 23.2 | 1 | 23.2 | - | - |
| $10^5$ | -0.55 | 0.75 | 0.52 | - | - | - | - | - | - | - | - | - | - | - |
| $10^6$ | 0.59 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | - | - |
| $10^7$ | 0.394 | 0.35 | 0.3 | 1 | 82.2 | 1 | 61.0 | - | - | - | - | - | - | - |
| $10^8$ | 0.9 | - | - | - | - | - | - | - | - | - | - | - | - | - |
| $10^9$ | 0.394 | 0.4 | - | - | - | - | - | - | - | - | - | - | - | - |
| $10^{10}$ | 0.9 | - | - | - | - | - | - | - | - | - | - | - | - | - |

some $i \in \{0, \ldots, k - 1\}$ and some state $s'$ with $F_i'[s'] > F_{i+1}'[s']$. Since $F_0, \ldots, F_k$ satisfy the chain-property and since $s$ is the only state where $F_i'$ and $F_{i+1}'$ might differ, we have $s' = s$. There are now two cases: Either $F_{i+1}[s] \leq \delta$ or $F_{i+1}[s] > \delta$.

If $F_{i+1}[s] \leq \delta$, we also have $F_i[s] \leq \delta$ (chain-property). Hence, we have $F_i'[s] = F_i[s]$ and $F_{i+1}'[s] = F_{i+1}[s]$. This implies $F_i'[s] \leq F_{i+1}'[s]$ since $F_0, \ldots, F_k$ satisfy the chain-property.

If $F_{i+1}[s] > \delta$, then $F_{i+1}'[s] = \delta$. Since $F_i'[s]$ is the minimum of $F_i[s]$ and $\delta$, we again derive that the chain property holds.

Frame-Safety. This case is immediate since we choose the minimum of $F_i[s]$ and $\delta$. This means that if $s = s_t$ and $\delta > \lambda$, we have $F_i'[s_t] = F_i[s_t]$ for all $i \in \{0, \ldots, k\}$. Hence, frame-safety continues to hold for $F_0', \ldots, F_k'$. Conversely, if $\delta \leq \lambda$, frame-safety continues to hold, as well.

Relative Inductiveness. First notice that the chain-property and monotonicity of $\Phi$ imply

$$\Phi(F_{i-1}) \leq \Phi(F_i) \quad \text{for all } i \in \{1, \ldots, k\}.$$ 

This and our assumption $\Phi(F_{k-1})[s] \leq \delta$ yields

$$\Phi(F_i)[s] \leq \delta \quad \text{for all } i \in \{0, \ldots, k - 1\}.$$ 

($\heartsuit$)
Now let $i \in \{1, \ldots, k\}$ and let $s' \in S$. We show $\Phi(F_{i-1}')[s'] \leq F_i'[s']$ by distinguishing the cases $s' = s$ and $s' \neq s$.

**The case $s' = s$.** First observe that

\[
F_{i-1}' \leq F_{i-1}
\]

implies

\[
\Phi(F_{i-1}') \leq \Phi(F_{i-1})
\]

(monotonicity of $\Phi$)

implies

\[
\Phi(F_{i-1}')[s] \leq \delta \quad \text{(and transitivity of $\leq$)}
\]

There are now two cases. Either $F_i'[s] = \delta$ or $F_i'[s] = F_i[s]$. If $F_i'[s] = \delta$, we have

\[
\Phi(F_{i-1}')[s] \leq \delta = F_i'[s] \leq F_i'[s].
\]

Since $F_i'[s]$ is the minimum of $F_i[s]$ and $\delta$, $F_i'[s] = F_i[s]$ implies $F_i[s] \leq \delta$. By the chain property, we then also have $F_{i-1}[s] \leq \delta$. Hence, we have $F_{i-1}' = F_{i-1}$ and $F_i' = F_i$, which gives us

\[
\Phi(F_{i-1}')[s] = \Phi(F_{i-1})[s] \quad (F_{i-1}' = F_{i-1})
\]

\[
\leq F_i[s] \quad \text{(chain-property for $F_0, \ldots, F_k$)}
\]

\[
= F_i'[s] \quad (F_i' = F_i)
\]

\[
\leq F_i'[s].
\]

**The case $s' \neq s$.** In this case, we have $F_i'[s'] = F_i[s']$. Furthermore, monotonicity of $\Phi$ and $F_{i-1}' \leq F_{i-1}$ yields $\Phi(F_{i-1}')[s'] \leq \Phi(F_{i-1})$. Together, this gives us

\[
\Phi(F_{i-1}')[s'] \leq \Phi(F_{i-1})[s'] \leq F_i[s'] = F_i'[s'] \leq F_i'[s'].
\]

This completes the proof.

**B.3 Proof of Lemma [7]**

**Proof.** We prove soundness and completeness separately.

\[\text{\textit{Soundness.}}\] If PrIC3 terminates inside the loop, then soundness is guaranteed by the soundness of PrIC3\textsubscript{H} and CheckRefutation. Otherwise, i.e., if PrIC3 terminates in line 10, then $\text{touched} = S$ and our assumption yields

\[\Omega(s_I) \leq \lambda \iff \Prmax(s_I \models \diamond B) \leq \lambda.\]

The case $s' = s$. In this case, we have $F_i'[s'] = F_i[s']$. Furthermore, monotonicity of $\Phi$ and $F_{i-1}' \leq F_{i-1}$ yields $\Phi(F_{i-1}')[s'] \leq \Phi(F_{i-1})$. Together, this gives us

\[\Phi(F_{i-1}')[s'] \leq \Phi(F_{i-1})[s'] \leq F_i[s'] = F_i'[s'] \leq F_i'[s']\]

This completes the proof.

**B.4 Proof of Recovery Statement [1]**

**Proof.** This is a consequence of the well-known fact that [7] Chap. 10

\[\Prmax(s_I \models \diamond B) = 0 \iff s_I \not\models \exists B.\]

That is, the maximal probability to reach a state in $B$ from the initial state $s_I$ is 0 iff no state in $B$ is reachable from $s_I$ in the graph structure underlying the MDP $\mathcal{M}$. 

B.5 Proof of Recovery Statement

Proof. We prove the recovery statement under the reasonable assumption that the heuristic $H$ is adequate since otherwise we do not recover standard IC3. By Recovery Statement$^3$ all obligations $(i, s, \delta)$ spawned by $\text{Strengthen}_H$ satisfy $\delta = 0$. Hence, all frames $F$ computed by $\text{PrIC3}_H$ satisfy

$$\forall s \in S: F[s] \in \{0, 1\}.$$  

For our convenience, we therefore regard frames as sets of states.

We now proceed by contradiction. Assume that $\text{PrIC3}_H$ terminates in line 8 after the $k$th call to $\text{Strengthen}_H$. Our goal is to show that $\text{oldSubsystem} = \text{subsystem}$ implies $F_1 = F_2$, which means that $\text{PrIC3}_H$ has terminated in line 7, contradicting our assumption. We rely on two observations:

Observation 1. Since $\text{PrIC3}_H$ terminates in line 8, procedure $\text{Strengthen}_H$ resolved all obligations spawned, i.e., $\text{Strengthen}_H$ returned $\text{success} = \text{true}$ in every iteration. This implies that every state touched by $\text{Strengthen}_H$ is removed from $F_1$: Denote by $F_{j,i}$ the frame $F_j$ after the $i$th call to $\text{Strengthen}_H$ and by $\text{subsystem}_i$ the subsystem returned by the $i$th call to strengthen. We have

$$F_{1,i} = S \setminus \text{subsystem}_i.$$  

That is, every state touched by $\text{Strengthen}_H$ is removed from $F_1$, which is an immediate consequence of the chain-property (cf. Definition$^3$) and the fact that all obligations are resolved. Finally, our assumption that $\text{oldSubsystem} = \text{subsystem}$ holds on iteration $k$ gives us

$$F_{1,k-1} = F_{1,k}.$$  

Observation 2. Denote by $\text{Reach}^{\leq i}$ the states reachable in at most $i$ steps from initial state $s_I$. As it is the case for standard (reverse) IC3, $\text{Strengthen}_H$ refines the frames in such a way that

$$\forall 1 \leq i \leq k: \forall 1 \leq j \leq i: F_{j,i} = S \setminus \text{Reach}^{\leq i-j}.$$  

Let us now consider the frames $F_{1,k}$ and $F_{2,k}$. Since $F_{1,k-1} = F_{1,k}$ by Observation 1, we have $\text{Reach}^{\leq k-2} = \text{Reach}^{\leq k-1}$ by Observation 2. This gives us

$$F_{1,k} = \text{Reach}^{\leq k-1} = \text{Reach}^{\leq k-2} = F_{2,k},$$  

(by Observation 1 and 2)  

(by Observation 2)

which is what we had to show.
B.6 Proof of Recovery Statement 3

Proof. Let $\lambda = 0$, and let $\mathcal{H}$ be an adequate heuristic. We show that

$$ I = \forall (i, s, \delta) \in Q: \delta = 0 $$

is an invariant of the loop in Algorithm 2, which implies the claim.

Initialization. Since $\lambda = 0$, invariant $I$ holds at the beginning of the loop.

Consecutive. Assume that $I$ holds at the beginning of some iteration. This implies that after line 3, we have $\delta = 0$. Now assume we spawn new obligations, i.e. that line 7 is executed. The check in line 4 thus evaluated to false, which means $s \notin B$. Since $\mathcal{H}$ is adequate, it spawns $\delta_1, \ldots, \delta_n$ such that

$$ \Phi_a \left( F \langle s_1 \mapsto \delta_1 \rangle \ldots \langle s_n \mapsto \delta_n \rangle \right) [s] \leq \delta \quad \text{(since $\mathcal{H}$ is adequate)}$$

iff

$$ \sum_{i=1}^{n} P(s, a, s_i) \cdot \delta_i \leq 0 \quad \text{($s \notin B$ and $\text{Succs}(s, a) = \{s_1, \ldots, s_n\}$)}$$

iff

$$ \delta_1 = 0 \land \ldots \land \delta_n = 0 \quad \text{(since $\delta_1, \ldots, \delta_n \geq 0$)}$$

This completes the proof.

B.7 Proof of Recovery Statement 4

Proof. We first show that for every obligation $(i, s, \delta) \in Q$, $Q$.touched() contains all states on some path from the initial state $s_I$ to state $s$. At the beginning of the loop, this holds trivially since $Q = \{(k, s_I, \delta)\}$. Furthermore, every loop iteration preserves the desired property since:

1. New obligations consist of successors of states in the queue only (line 8), and
2. state $s$ is reenqueued if obligations for its successors are added to the queue (line 9).

Now let $\lambda = 0$, and let $\mathcal{H}_0$ be the adequate heuristic that maps every state to 0. Recall from Recovery Statement 3 that for every obligation $(i, s, \delta) \in Q$ it holds that $\delta = 0$. Hence, if the check in line 4 evaluates to true, we must have $s \in B$. Since $Q$.touched() contains a path from the initial state to state $s$, the recovery statement follows.

B.8 Proof of Recovery Statement 5

Proof. This is a consequence of Recovery Statements 2 and 4. We show that PrIC3 terminates after the first call to PrIC3$\mathcal{H}$ by distinguishing the cases where PrIC3$\mathcal{H}$ returns safe = true and where PrIC3$\mathcal{H}$ returns safe = false.

PrIC3$\mathcal{H}$ returns safe = true. In this case, we have nothing to show since PrIC3 immediately terminates in line 5.
PrIC3 returns false. By Recovery Statement 2, PrIC3 never terminates in line 8. Hence, PrIC3 has terminated in line 4. Now, by Recovery Statement 4, subsystem contains a path from the initial state \( s_I \) to some state \( s \in B \). Hence, the probability to reach some bad state in the subMDP \( M_{\text{subsystem}} \) is larger than \( \lambda = 0 \), which yields CheckRefutation(subsystem) to return true and PrIC3 to terminate in line 5.