

Probabilistic Programming

Lecture #8+#9: Loop Invariants

Joost-Pieter Katoen



Software Modeling
and Verification Chair

RWTH AACHEN
UNIVERSITY

RWTH Lecture Series on Probabilistic Programming 2018

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

Motivation

- ▶ Reasoning about loops is the **hardest task** in program verification
- ▶ Why?
 - ▶ Weakest preconditions of loops are defined as fixed points
 - ▶ They can be approximated iteratively
 - ▶ **But:** Recognise a pattern to yield a closed-form formula for taking a loop n times
 - ▶ Taking the limit yields the required fixed point

These last two steps are the source of **undecidability**

- ▶ “Practical” approach: capture the effect of a loop by a **loop invariant**

A loop invariant is a property of a program loop that is true before (and after) each iteration.

Loop invariants à la Dijkstra, Floyd, Hoare

Loop invariants

Recall that for while-loops we have:

$$wlp(\text{while}(G)\{P\}, F) = \text{gfp } X. (G \wedge wlp(P, X)) \vee (\neg G \wedge F)$$

To determine the effect ~~of a~~ of a while-loop, one exploits an “invariant” $I \in \mathbb{P}$

Loop invariants

Recall that for while-loops we have:

$$wlp(\text{while}(G)\{P\}, F) = \text{gfp } X. (G \wedge wlp(P, X)) \vee (\neg G \wedge F)$$

To determine the effect of a while-loop, one exploits an “invariant” $I \in \mathbb{P}$

Loop invariant

Predicate $I \in \mathbb{P}$ is a **loop invariant** if it satisfies:

1. $G \Rightarrow I$
2. $\neg G \wedge I \Rightarrow F$, and
3. $G \wedge I \Rightarrow wlp(P, I)$.

Satisfaction of I is invariant under (guarded) iteration of the loop body P .

while ($x < 10$) $\{ x++ \}$

$$F = (x = 10)$$

$$G = x < 10$$

$I = x \leq 10$ is a loop invariant.

✓ a. $x < 10 \Rightarrow x \leq 10$

✓ b. $\neg(x < 10) \wedge x \leq 10 \Rightarrow x = 10$

✓ c. $\underbrace{x < 10 \wedge x \leq 10}_{x < 10} \Rightarrow \text{wlp } (P, \underbrace{x \leq 10}_{=I})$
 $x++$

Characteristic functions for loops

Recall:

$$wp(\text{while } (\textcolor{blue}{G})\{ P \}, \textcolor{red}{f}) = \text{lfp } X. \underbrace{([\textcolor{blue}{G}] \cdot wp(P, X) + [\neg \textcolor{blue}{G}] \cdot \textcolor{red}{f})}_{\text{characteristic function } \Phi_{\textcolor{red}{f}}(X) \text{ for } wp}$$

and

$$wlp(\text{while } (\textcolor{blue}{G})\{ P \}, \textcolor{red}{f}) = \text{gfp } X. \underbrace{([\textcolor{blue}{G}] \cdot wlp(P, X) + [\neg \textcolor{blue}{G}] \cdot \textcolor{red}{f})}_{\text{characteristic function } \Psi_{\textcolor{red}{f}}(X) \text{ for } wlp}$$

Loop invariants

so these are predicates
(no expectations)

wlp

For $I, F \in \mathbb{P}$ and probabilistic loop while($G\{P\}$) it holds:

$$(\underbrace{\neg G \wedge I \Rightarrow F \text{ and } G \wedge I \Rightarrow wlp(P, I)}_{\text{conditions 2.+3. of being an invariant}}) \text{ iff } [I] \sqsubseteq \Psi_{[F]}([I])$$

where $\Psi_{[F]}$ is the wlp-characteristic function of the probabilistic loop for postcondition $[F]$.

Proof.

On the black board. □

Example of a loop invariant.

$$[I] \leq \Phi_{[F]}([I])$$

$$\neg G \wedge I \Rightarrow F$$

$$\text{iff } [\neg G] \cdot [I] \leq [F]$$

$$\text{iff } [\neg G] \cdot [I] \leq [\neg G] \cdot [F]$$

Now derive:

$$G \wedge I \Rightarrow wlp(P, I)$$

$$\text{iff } [G] \cdot [I] \leq wlp(P, [I])$$

$$\text{iff } [G] \cdot [I] \leq [G] \cdot wlp(P, [I])$$

$$\text{iff } [\neg G] \cdot [I] + [G \cdot I] \leq [G] \cdot wlp(P, [I])$$

$$\text{iff } [I] \leq \Phi_{[F]}([I])$$

$$+ [\neg G] \cdot [F]$$
$$= \Phi_{[F]}([I])$$

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

Probabilistic invariants

$$[G] \cdot \text{wp}(P, X) + [\neg G] \cdot f$$

Probabilistic invariants

Let Φ_f be the wp-characteristic function of $P' = \text{while}(G)\{P\}$ with respect to post-expectation $f \in \mathbb{E}$ and let $I \in \mathbb{E}$. Then:

Probabilistic invariants

Probabilistic invariants

Let Φ_f be the wp-characteristic function of $P' = \text{while}(G)\{P\}$ with respect to post-expectation $f \in \mathbb{E}$ and let $I \in \mathbb{E}$. Then:

1. I is a wp-superinvariant of P' w.r.t. f iff $\Phi_f(I) \leq I$.

Probabilistic invariants

Probabilistic invariants

Let Φ_f be the wp-characteristic function of $P' = \text{while}(G)\{P\}$ with respect to post-expectation $f \in \mathbb{E}$ and let $I \in \mathbb{E}$. Then:

1. I is a wp-superinvariant of P' w.r.t. f iff $\Phi_f(I) \leq I$.
2. I is a wp-subinvariant of P' w.r.t. f iff $I \leq \Phi_f(I)$.

Probabilistic invariants

Probabilistic invariants

Let Φ_f be the wp-characteristic function of $P' = \text{while}(G)\{P\}$ with respect to post-expectation $f \in \mathbb{E}$ and let $I \in \mathbb{E}$. Then:

1. I is a wp-superinvariant of P' w.r.t. f iff $\Phi_f(I) \leq I$.
2. I is a wp-subinvariant of P' w.r.t. f iff $I \leq \Phi_f(I)$.

Sub- and superinvariants for wlp are defined analogously (but are bounded, i.e., then $I \in \mathbb{E}_{\leq 1}$, and Φ_f is replaced by Ψ_f .)

Lemma

$[G] \cdot I \leq wp(P, I)$ iff $I \leq \Phi_{[\neg G]}(I)$ for all $I \in \mathbb{E}$, and pGCL program P .

Proof.

Left as an exercise. □

$P ::= \text{while } (c=0) \{ x++ [p] c:=1 \}$

Claim $I = x + [c=0] \cdot \frac{P}{1-p}$ is an invariant of P wrt. $f = x$.

$\xrightarrow{\quad}$
subinvariant +
superinvariant

we prove that I is a superinvariant

$$\Phi_f(I) \leq I.$$

$$\Phi_f(I) = [c \neq 0] \cdot x + [c=0] \text{ wp } (x++ [p] c:=1, I)$$

$$= [c \neq 0] \cdot x + [c=0] \left(p \cdot I(x := x+1) + (1-p) \cdot I(c := 1) \right)$$

= -----

$$[c \neq 0] \times [c=0] \left(\cancel{px+p} + \frac{p^2}{1-p} + \cancel{x-px} \right)$$

$$= x + [c=0] \left(\underbrace{\frac{p(1-p) + p^2}{1-p}}_{\frac{p}{1-p}} \right)$$

$$\Rightarrow x + [c=0] \frac{p}{1-p} \text{ is a superinvariant}$$

As in the above derivation we only have equalities

I is a wp-subinvariant too.

Induction for upper bounds on wp

Induction on complete lattices (Park's lemma)

Let (D, \sqsubseteq) be a complete lattice and $\Phi : D \rightarrow D$ continuous. Then:

$$\forall d \in D. \quad \Phi(d) \sqsubseteq d \quad \text{implies} \quad \text{lfp } \Phi \sqsubseteq d.$$

Applying this induction principle yields upper bounds on weakest pre-expectations.

Upper bounds on weakest pre-expectations

For $\text{while}(G)\{P\}$ and $f, I \in \mathbb{E}$ we have:

$$\underbrace{\Phi_f(I) \leq I}_{\text{wp-superinvariant}} \quad \text{implies} \quad \text{wp}(\text{while}(G)\{P\}, f) \leq I$$

Every wp-superinvariant of a loop for f
is an upper bound to the wp of the loop (and f).

Example $P = c := 1; \text{while}(c) \{ c := 0 [\frac{1}{2}] x++ \}$
 $f = x$
 $I = x + [c=1]$ is a superinvariant of P w.r.t. f .

$$\begin{aligned}\underline{\Phi}_x^f(I) &= \underline{\Phi}(x + [c=1]) \\ &= [c \neq 1] \cdot \underline{x} + [c=1] \sum \underline{(x + [0=1])} + \underline{x+1 + [c=1]} \\ &= x + [c=1](0+1+1) \cdot \frac{1}{2} = I\end{aligned}$$

Theorem $\text{wp}(\text{while} \dots, x) \leq x + [c=1] \quad (*)$

For P : $\text{wp}[c := 1; \text{while} \dots, x] = \dots \leq \overset{\uparrow}{x + [1=1]} = \underline{\underline{x+1}}$

$$\begin{aligned}&\text{wp}(c := 1, \underbrace{\text{wp}(\text{while} \dots, x)}) \\ &\leq x + [c=1] \quad \text{by monotonicity of wp}\end{aligned}$$

Co-induction for lower bounds on wlp

Co-induction on complete lattices (Park's lemma)

Let (D, \sqsubseteq) be a complete lattice and $\Phi : D \rightarrow D$ continuous. Then:

$$\forall d \in D. \quad d \sqsubseteq \Phi(d) \quad \text{implies} \quad d \sqsubseteq \text{gfp } \Phi.$$

Applying this induction principle yields lower bounds on weakest liberal pre-expectations.

Lower bounds on weakest liberal pre-expectations

For $\text{while}(G)\{P\}$ and $f, I \in \mathbb{E}_{\leq 1}$ we have:

$$\underbrace{I \leq \Psi_f(I)}_{\text{wlp-subinvariant}} \quad \text{implies} \quad I \leq \text{wlp}(\text{while}(G)\{P\}, f)$$

Every wlp-subinvariant of a loop for f
is a lower bound to the wlp of the loop (and f).

Example $P_0 := c:=1 ; \text{while } (c) \{ \text{div } [\frac{1}{2}] x++ ; \text{skip } [\frac{1}{2}] c:=0 \}$
 $f = [x \text{ even}]$

claim: $I = [c \neq 1] \cdot [x \text{ even}] +$
 $[c=1] \cdot \left(\frac{2}{3} + \frac{4[x \text{ odd}]}{15} + \frac{[x \text{ even}]}{15} \right)$

is a wlp-subinvariant of P

need: $\Phi(I) = I$

Theorem: $I \leq \text{wlp}(\text{while } \dots, x)$

Hence $\text{wlp}(P, x) = \text{wlp}(c:=1, \underbrace{\text{wlp}(\text{while } \dots, x)}_{I \leq \dots})$
 $\geq \frac{2}{3} + \frac{4[x \text{ odd}]}{15} + \frac{[x \text{ even}]}{15}$

Verification of loops (1)

The following procedure can be followed for induction and co-induction:

1. Find an appropriate loop invariant I
2. Push I through the characteristic function of the loop once, i.e., compute $\Phi(I)$
3. Check whether this took us down or up in the partial order \leq :
 - 3.1 $\Phi(I) \leq I$, for induction, or
 - 3.2 $I \leq \Phi(I)$, for co-induction.

The key difficulty is to find an appropriate invariant I . This is undecidable.

Remarks about unsound versions of (co-)induction

Let (D, \sqsubseteq) be a complete lattice and $\Phi : D \rightarrow D$ continuous. The following statements are **not** valid:

$$\Phi(d) \sqsubseteq d \Rightarrow \text{lfp } \Phi \sqsubseteq d \quad \begin{matrix} \text{lower bounds} \\ \text{of up} \end{matrix}$$

$$\forall d \in D. \quad d \sqsubseteq \Phi(d) \text{ implies } d \sqsubseteq \text{lfp } \Phi.$$

and

$$\forall d \in D. \quad \Phi(d) \sqsubseteq d \text{ implies } \text{gfp } \Phi \sqsubseteq d. \quad \begin{matrix} \text{upper bounds} \\ \text{of wfp} \end{matrix}$$

$$d \sqsubseteq \Phi(d) \Rightarrow d \sqsubseteq \text{gfp } \Phi$$

Remarks about unsound versions of (co-)induction

Let (D, \sqsubseteq) be a complete lattice and $\Phi : D \rightarrow D$ continuous. The following statements are **not** valid:

$$\forall d \in D. \quad d \sqsubseteq \Phi(d) \quad \text{implies} \quad d \sqsubseteq \text{lfp } \Phi.$$

and

$$\forall d \in D. \quad \Phi(d) \sqsubseteq d \quad \text{implies} \quad \text{gfp } \Phi \sqsubseteq d.$$

As a consequence, co-induction for lower bounds on wp of loops and induction on upper bounds on wlp of loops is **unsound**.

Remarks about unsound versions of (co-)induction

Let (D, \sqsubseteq) be a complete lattice and $\Phi : D \rightarrow D$ continuous. The following statements are **not** valid:

$$\forall d \in D. \quad d \sqsubseteq \Phi(d) \quad \text{implies} \quad d \sqsubseteq \text{lfp } \Phi.$$

and

$$\forall d \in D. \quad \Phi(d) \sqsubseteq d \quad \text{implies} \quad \text{gfp } \Phi \sqsubseteq d.$$

As a consequence, co-induction for lower bounds on wp of loops and induction on upper bounds on wlp of loops is unsound.

Counterexample

On the black board.

Counter example

while ($c=1$) { $(c:=0 \ [\frac{1}{2}] \ x++) ; \ k++$ }

$f = x$

$$\underline{\Phi}(x) = [c \neq 1] \cdot x + [c = 1] \cdot \left(\frac{1}{2} \times [k := k+1, c := 0] + \frac{1}{2} \times [x := x+1, k := k+1] \right)$$

Claim: for every $a > 0$

$$I_a = x + [c = 1] (2^{k+a} + 1)$$

is a fixed point of $\underline{\Phi}$. (Please verify)

Now: $d < b$ then $I_d < I_b$

Thus if e.g. $I_b \leq \underline{\Phi}(I_b)$, we cannot conclude

that $I_b \leq \text{lfp } \underline{\Phi}$ since I_d is also a
fixed point

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

ω -invariants

ω -invariants

Let $n \in \mathbb{N}$, $f \in \mathbb{E}$ and Φ_f be the wp-characteristic function of the loop
while($G\{P\}$). $I_0 \leq I_1 \leq I_2 \leq I_3 \dots$

The monotonically increasing¹ sequence $(I_n)_{n \in \mathbb{N}}$ is a **wp- ω -subinvariant** of
the loop w.r.t. f iff

$$I_0 \leq \Phi_f(0) \quad \text{and} \quad I_{n+1} \leq \Phi_f(I_n) \quad \text{for all } n.$$

In a similar way, **wlp- ω -superinvariants** are defined, where $f, I_n \in \mathbb{E}_{\leq 1}$,
 $(I_n)_{n \in \mathbb{N}}$ is monotonically decreasing, and Φ_f is replaced by Ψ_f .

$$I_0 \geq I_1 \geq I_2 \dots$$

$$\Psi_f(I_1) \leq I_0 \quad \text{and} \quad \Psi_f(I_n) \leq I_{n+1}$$

¹But not necessarily strictly increasing.

Bounds on loops using ω -invariants

$$I_0 \leq \Phi_f(0) \quad I_{n+1} \leq \Phi_f(I_n)$$

Theorem

1. Let $(I_n)_{n \in \mathbb{N}}$ be a wp- ω -subinvariant of $\text{while}(G)\{P\}$ w.r.t. $f \in \mathbb{E}$. Then:

$$\sup_{n \in \mathbb{N}} I_n \leq \text{wp}(\text{while}(G)\{P\}, f).$$

2. Let $(I_n)_{n \in \mathbb{N}}$ be a wlp- ω -superinvariant of $\text{while}(G)\{P\}$ w.r.t. f . Then:

$$\text{wlp}(\text{while}(G)\{P\}, f) \leq \inf_{n \in \mathbb{N}} I_n.$$

Proof.



Claim,

$$\boxed{\forall n \in \mathbb{N}. \quad I_n \leq \underline{\Phi}_f^{n+1}(\underline{o})}$$

for ω -wp subinvariant $(I_n)_{n \in \mathbb{N}}$.

$$\sup_{n \in \mathbb{N}} I_n \leq \sup_{n \in \mathbb{N}} \underline{\Phi}_f^{n+1}(\underline{o})$$

$$= \sup_{n \in \mathbb{N}} \underline{\Phi}_f^n(\underline{o})$$

$$= \text{Lfp } \underline{\Phi}_f$$

$$= \text{up (while ..., f)} \quad \square$$

Verification of loops (2)

The following procedure can be followed using ω -sub-/superinvariants:

1. Find an appropriate ω -invariant, i.e., a sequence $(I_n)_{n \in \mathbb{N}}$
2. Check that $(I_n)_{n \in \mathbb{N}}$ is indeed an ω -invariant:
 - 2.1 Push I_n through the characteristic function
 - 2.2 Check whether this took us above I_{n+1} (for wp) or below I_{n+1} (for wlp)
in the partial order \leq
3. Find the supremum (for wp) or the infimum (for wlp) of $(I_n)_{n \in \mathbb{N}}$

In addition to finding appropriate invariants I_n , we have to reason about the limits of the ω -invariants. This is undecidable too.

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

Total correctness proof rules for loops

[McIver &
Morgan 2005]

Total correctness proof rules for loops

Total correctness proof rules for loops

Let $f \in \mathbb{E}$ with $f \leq k$, for some $k \in \mathbb{N}$, and let $J \in \mathbb{E}$ be k -bounded too such that $I \in \mathbb{E}$ defined by: $I = [\neg G] \cdot f + [G] \cdot J$.

$$\forall s \in S . \quad f(s) \leq k$$

$$J(s) \leq k$$

Total correctness proof rules for loops

Total correctness proof rules for loops

Let $f \in \mathbb{E}$ with $f \leq k$, for some $k \in \mathbb{N}$, and let $J \in \mathbb{E}$ be k -bounded too such that $I \in \mathbb{E}$ defined by: $I = [\neg G] \cdot f + [G] \cdot J$. Then it holds:

1. If $I = [F]$ for some predicate $F \in \mathbb{P}$, then:

$$T \cdot I \leq wp(\text{while}(G)\{P}, f)$$

where $T = wp(\text{while}(G)\{P}, 1)$ is the loop's termination probability.

2. If $[F] \leq T$ for some predicate $F \in \mathbb{P}$, then:

$$[F] \cdot I \leq wp(\text{while}(G)\{P}, f)$$

3. If $\varepsilon \cdot I \leq T$ for some $\varepsilon > 0$, then:

$$I \leq wp(\text{while}(G)\{P}, f).$$

Almost-surely terminating loops

$\Pr \{ \text{termination of } \text{while}(G)\{P\} \} = 1.$

Proof rules for a.s.-terminating loops

Let $\text{while}(G)\{P\}$ be almost-surely terminating, i.e., $\text{wp}(\text{while}(G)\{P\}, \mathbf{1}) = 1$, and let $I \in \mathbb{E}_{\leq 1}$. Then:

for all inputs

1.

$$I \leq \Phi_f(I) \text{ implies } I \leq \text{wp}(\text{while}(G)\{P\}, f).$$

2.

$$\Psi_f(I) \leq I \text{ implies } \text{wlp}(\text{while}(G)\{P\}, f) \leq I.$$

$\text{while}(c) \{ c := [\frac{1}{2}] \leftrightarrow \}$

$$I = x + [c=1] \frac{P}{1-p}$$

Bound refinement

Bound refinement

Let loop $\text{while}(G)\{P\}$, $f, I \in \mathbb{E}$. Then:

1. If $\Phi_f(I) \leq I$:

\neq

$wp(\text{while}(G)\{P\}, f) \leq I$ implies $wp(\text{while}(G)\{P\}, f) \leq \Phi_f(I)$.

$<$

let $\text{wp}(\text{while } . . , f) \subseteq I$.

iff $\text{lfp } \Phi \subseteq I$

$\Rightarrow \Phi(\text{lfp } \Phi) = \Phi(I)$

$\Rightarrow \underbrace{\text{lfp } \Phi}_{\Phi(I)} \subseteq \Phi(I)$

$\Leftarrow \text{wp}(\text{while } . .) \subseteq \Phi(I)$

Bound refinement

Bound refinement

Let loop $\text{while}(G)\{P\}$, $f, I \in \mathbb{E}$. Then:

1. If $\Phi_f(I) \leq I$:

$$wp(\text{while}(G)\{P\}, f) \leq I \quad \text{implies} \quad wp(\text{while}(G)\{P\}, f) \leq \Phi_f(I).$$

2. If $I \leq \Phi_f(I)$:

$$I \leq wp(\text{while}(G)\{P\}, f) \quad \text{implies} \quad \Phi_f(I) \leq wp(\text{while}(G)\{P\}, f).$$

If $\Phi_f(I) \neq I$, we thus obtain tighter upper and lower bounds, respectively.

The sequence $\Phi(I), \Phi^2(I), \Phi^3(I), \dots$ converges.

For upper bounds to the greatest fixed point that is below (or equal to) I .

(This fixed point itself is an upper bound too.)

This is the Tarski-Kantorovich fixpoint principle.

Overview

- 1 Motivation
- 2 Probabilistic invariants
- 3 ω -Invariants
- 4 Proof rules for loops
- 5 Invariant synthesis

Invariant synthesis for linear programs

- right-hand sides of assignments
are linear expressions

$$x := x + y + 20z$$

~~$$x := x^2 + y^3$$~~

- guards must be linear too

Invariant synthesis for linear programs

1. Speculate that a loop invariant can be expressed as linear expression:

template $\underbrace{[\alpha_1 \cdot x_1 + \dots + \alpha_n \cdot x_n + \alpha_{n+1} \ll 0]}_{\text{qualitative invariant}} \cdot \underbrace{(\beta_1 \cdot x_1 + \dots + \beta_n \cdot x_n + \beta_{n+1})}_{\text{quantitative invariant}}$

- ▶ where n is at most the number of program variables in the program
- ▶ x_i are program variables
- ▶ α_i, β_i are real-valued invariant-template variables
- ▶ $\ll \in \{<, \leq\}$ is a binary comparison operator

Invariant synthesis for linear programs

$$\alpha_1 \leq \alpha_2 + \alpha_3$$

1. Speculate that a loop invariant can be expressed as linear expression:

$$[\alpha_1 \cdot x_1 + \dots + \alpha_n \cdot x_n + \alpha_{n+1} \ll 0] \cdot (\beta_1 \cdot x_1 + \dots + \beta_n \cdot x_n + \beta_{n+1})$$

- ▶ where n is at most the number of program variables in the program
- ▶ x_i are program variables
- ▶ α_i, β_i are real-valued invariant-template variables
- ▶ $\ll \in \{<, \leq\}$ is a binary comparison operator

2. Transform these numerical constraints into non-linear FO formulas.
3. Use constraint solving techniques to obtain constraints on α_i, β_i .

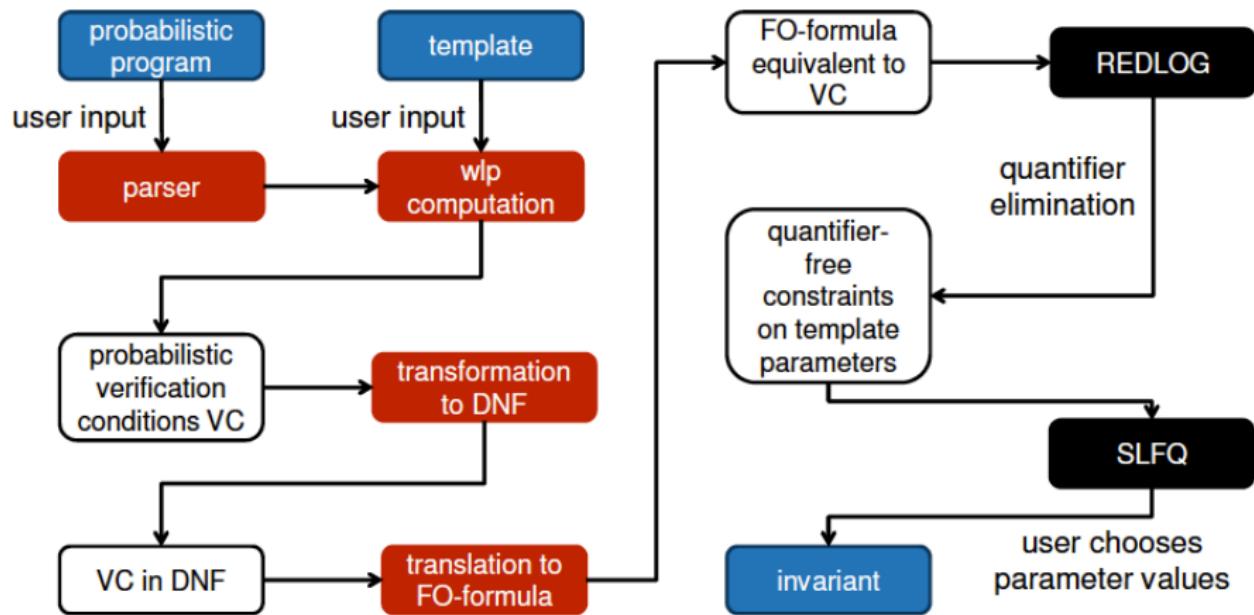
Soundness and completeness

For any **linear** probabilistic program and **linear** loop invariant
this method will find

all parameter solutions that make the template valid, and no others.

$$\alpha, \beta$$

PRINSYS tool: Probabilistic invariant synthesis



moves.rwth-aachen.de/prinsys

Duelling cowboys: when does A win?

```
int cbDuel(float a, b) {
    int t := A;
    int c := 1;
    while (c = 1) {
        if (t = A) {
            (c := 0 [a] t := B);
        } else {
            (c := 0 [b] t := A);
        }
    }
    return t;
}
```

Duelling cowboys: when does A win?

```
int cbDuel(float a, b) {  
    int t := A;  
    int c := 1;  
    while (c = 1) {  
        if (t = A) {  
            (c := 0 [a] t := B);  
        } else {  
            (c := 0 [b] t := A);  
        }  
    }  
    return t;  
}
```

Aim: find expectation /

Satisfying $\textcolor{blue}{I} \leq [t = A]$ upon termination.

$$\overbrace{\text{survivor}}^{\text{---}} = f$$

Duelling cowboys: when does A win?

```

int cbDuel(float a, b) {
    int t := A;
    int c := 1;
    while (c = 1) {
        if (t = A) {
            (c := 0 [a] t := B);
        } else {
            (c := 0 [b] t := A);
        }
    }
    return t;
}

```

Aim: find expectation $\textcolor{blue}{I}$

Satisfying $\textcolor{blue}{I} \leq [t = A]$ upon termination.

Observation

On entering the loop, $c = 1$ and either $t = A$ or $t = B$.

Template suggestion

$$\begin{aligned}
 \textcolor{blue}{I} &= \underbrace{[t = A \wedge c = 0] \cdot 1}_{A \text{ wins duel}} \\
 &+ \underbrace{[t = A \wedge c = 1] \cdot \alpha}_{A's \text{ turn}} \\
 &+ \underbrace{[t = B \wedge c = 1] \cdot \beta}_{B's \text{ turn}} \\
 &\quad \vdots \\
 &= \textcolor{blue}{I} + \underbrace{[t = B \wedge c = 0]}_{\text{B's turn}} \cdot \gamma
 \end{aligned}$$

Duelling cowboys: when does A win?

Invariant template: $I = [t = A \wedge c = 0] \cdot 1 + [t = A \wedge c = 1] \cdot \alpha + [t = B \wedge c = 1] \cdot \beta$

Initially, $t = A \wedge c = 1$ and thus $\alpha = \Pr\{A \text{ wins duel}\}$.

Maximisation: $\beta = (1 - b) \cdot \alpha$ and $\alpha = \frac{a}{a + b - a \cdot b}$

Probabilistic loop invariant

$$I = [t = A \wedge c = 0] \cdot 1 + [t = A \wedge c = 1] \cdot \frac{a}{a + b - ab} + [t = B \wedge c = 1] \cdot \frac{(1 - b)a}{a + b - a \cdot b}$$

Annotated program for post-expectation [$t = A$]

```

1 int cowboyDuel(a, b) {
2   a  

3   c  

4   (t := A c);
5    $\langle [t = A] \cdot \frac{a}{a+b-ab} + [t = B] \cdot \frac{(1-b)a}{a+b-ab} \rangle$ 
6   c := 1;
7    $\langle [t = A \wedge c = 0] \cdot 1 + [t = A \wedge c = 1] \cdot \frac{a}{a+b-ab} + [t = B \wedge c = 1] \cdot \frac{(1-b)a}{a+b-ab} \rangle$ 
8   while (c = 1) {
9      $\langle [t = A \wedge c = 1] \cdot \frac{a}{a+b-ab} + [t = B \wedge c = 1] \cdot \frac{(1-b)a}{a+b-ab} \rangle$ 
10     $\langle [t = A \wedge c \neq 1] \cdot a + [t = A \wedge c = 1] \cdot \frac{a}{a+b-ab}$ 
11       $+ [t = B \wedge c = 0] \cdot (1 - b) + [t = B \wedge c = 1] \cdot \frac{(1-b)a}{a+b-ab} \rangle$ 
12    if (t = A) {
13      (c := 0 [a] t := B);
14    } else {
15      (c := 0 [b] t := A);
16    }
17     $\langle [t = A \wedge c = 0] \cdot 1 + [t = A \wedge c = 1] \cdot \frac{a}{a+b-ab} + [t = B \wedge c = 1] \cdot \frac{(1-b)a}{a+b-ab} \rangle$ 
18     $\langle [c \neq 1] \cdot \left( [t = A \wedge c = 0] \cdot 1 + [t = A \wedge c = 1] \cdot \frac{a}{a+b-ab} \right.$ 
19       $\left. + [t = B \wedge c = 1] \cdot \frac{(1-b)a}{a+b-ab} \right) \rangle$ 
20     $\langle [t = A] \rangle$ 
21    return t; // the survivor
22  }

```

Playing with geometric distributions

- ▶ X is a random variable, geometrically distributed with parameter p
- ▶ Y is a random variable, geometrically distributed with parameter q

Q: generate a sample x , say, according to the random variable $X - Y$

```
int XminY1(float p, q){ // 0 <= p, q <= 1
    int x := 0;
    bool flip := false;
    while (not flip) { // take a sample of X to increase x
        (x +:= 1 [p] flip := true);
    }
    flip := false;
    while (not flip) { // take a sample of Y to decrease x
        (x -=: 1 [q] flip := true);
    }
    return x; // a sample of X-Y
}
```

An alternative program

$$f = [x=22]$$

$$f = x$$

```

int XminY2(float p, q){
    int x := 0;
    bool flip := false;
    (flip := false [0.5] flip := true); // flip a fair coin
    if (not flip) {
        while (not flip) { // sample X to increase x
            (x += 1 [p] flip := true);
        }
    } else {
        flip := false; // reset flip
        while (not flip) { // sample Y to decrease x
            x -= 1;
            (skip [q] flip := true);
        }
    }
    return x; // a sample of X-Y
}

```

$\text{Geom}(p)$

$\text{Geom}(q)$

Program equivalence: $X - Y$

```
int XminY1(float p, q){
    int x, c := 0, 1;
    while (c) {
        (x +=: 1 [p] c := 0);
    }
    c := 1;
    while (c) {
        (x -=: 1 [q] c := 0);
    }
    return x;
}
```

$$P = \frac{1}{2} \quad Q = \frac{2}{3}$$

```
int XminY2(float p, q){
    int x := 0;
    (c := 0 [0.5] c := 1);
    if (c) {
        while (c) {
            (x +=: 1 [p] c := 0);
        }
    } else {
        c := 1;
        while (c) {
            x -=: 1;
            (skip [q] c := 0);
        }
    }
    return x;
}
```

Using wp, one can prove that the expectations of $f = x$ coincide if and only if $q = \frac{1}{2-p}$.

Program equivalence: $X - Y$

```

int XminY1(float p, q){
    int x, f := 0, 0;
    while (f = 0) {
        (x++ [p] f := 1);
    }
    f := 0;
    while (f = 0) {
        (x-- [q] f := 1);
    }
    return x;
}

```

11

12

```

int XminY2(float p, q){
    int x, f := 0, 0;
    (f := 0 [0.5] f := 1);
    if (f = 0) {
        while (f = 0) {
            (x++ [p] f := 1);
        }
    } else {
        f := 0;
        while (f = 0) {
            x--;
            (skip [q] f := 1);
        }
    }
    return x;
}

```

21

22

Using template $I = x + [f = 0] \cdot \alpha$ we find:

$$\alpha_{11} = \frac{p}{1-p}, \alpha_{12} = -\frac{q}{1-q}, \alpha_{21} = \alpha_{11} \text{ and } \alpha_{22} = -\frac{1}{1-q}.$$

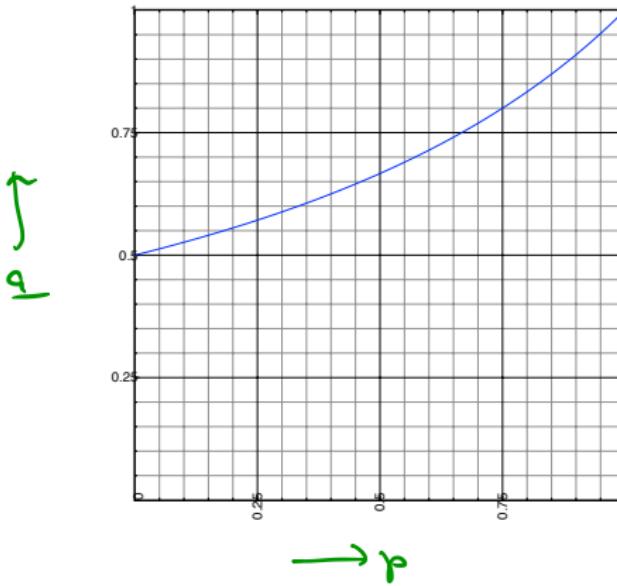
Program equivalence: $X - Y$

```
int XminY1(float p, q){
    int x, f := 0, 0;
    while (f = 0) {
        (x++ [p] f := 1);
    }
    f := 0;
    while (f = 0) {
        (x-- [q] f := 1);
    }
    return x;
}
```

```
int XminY2(float p, q){
    int x, f := 0, 0;
    (f := 0 [0.5] f := 1);
    if (f = 0) {
        while (f = 0) {
            (x++ [p] f := 1);
        }
    } else {
        f := 0;
        while (f = 0) {
            x--;
            (skip [q] f := 1);
        }
    }
    return x;
}
```

Expected value of x is $\frac{p}{1-p} - \frac{q}{1-q}$ and $\frac{p}{2(1-p)} - \frac{1}{2(1-q)}$.

Graphically this means ...



Both programs yield the same expected outcome for x all points on the curve $q = \frac{1}{2-p}$.
(and on no other points)