

# Probabilistic Programming

## Lecture #11: Reasoning About Loops

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RWTH Lecture Series on Probabilistic Programming 2022-23

## Overview

- 1 Motivation
- 2 Qualitative invariants
- 3 Probabilistic invariants
- 4 Upper bounds on loops
- 5 Lower bounds on loops
- 6 Program equivalence using loop invariants

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## 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  $k$  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 loop iteration.

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## Example

## Loop invariants à la Dijkstra

Recall that for while-loops we have for  $F \in \mathbb{P}$ :

$$wlp[[\text{while}(\varphi)\{P\}]](F) = \text{gfp } X. (\varphi \wedge wlp[[P]](X) \vee (\neg\varphi \wedge F))$$

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** w.r.t. postcondition  $F \in \mathbb{P}$  if it satisfies:

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

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

## Characteristic functions for probabilistic loops

Let  $P$  be a probabilistic program in pGCL

Recall for expectation  $f \in \mathbb{E}$ :

$$wp[[\text{while}(\varphi)\{P\}]](f) = \text{lfp } X. \underbrace{([\varphi] \cdot wp[[P]](X) + [\neg\varphi] \cdot f)}_{\text{characteristic function } \Phi_f(X) \text{ for } wp}$$

and

$$wlp[[\text{while}(\varphi)\{P\}]](f) = \text{gfp } X. \underbrace{([\varphi] \cdot wlp[[P]](X) + [\neg\varphi] \cdot f)}_{\text{characteristic function } \Psi_f(X) \text{ for } wlp}$$

## Loop invariants à la Dijkstra for pGCL

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

$$((\neg\varphi \wedge I) \Rightarrow F \text{ and } (\varphi \wedge I) \Rightarrow \text{wlp}[[P]](I)) \text{ iff } [I] \sqsubseteq \Psi_{[F]}([I])$$

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

### Proof.

On the black board. □

## Probabilistic invariants

Let  $\Phi_f$  be the wp-characteristic function of  $P' = \text{while}(\varphi)\{P\}$  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  $\Phi_f(I) \sqsubseteq I$ .
2.  $I$  is a **wp-subinvariant** of  $P'$  w.r.t.  $f$  iff  $I \sqsubseteq \Phi_f(I)$ .

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

### Lemma

$[\varphi] \cdot I \sqsubseteq \text{wlp}[[P]](I) \text{ iff } I \sqsubseteq \Phi_{[\neg\varphi] \cdot I}(I) \text{ for all } I \in \mathbb{E} \text{ and pGCL program } P.$

### Proof.

Left as an exercise. □

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## Duelling cowboys: when does A win?

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

Probabilistic loop invariant w.r.t. postcondition  $[t = A]$

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

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## Pictorially

## Induction for upper bounds on wp

Recall:

$$wp[\text{while } (\varphi) \{ P \}](f) = \text{lfp } X. \underbrace{([\varphi] \cdot wp[P](X) + [\neg\varphi] \cdot f)}_{\Phi_f(X)}$$

Park's lemma: let  $(D, \sqsubseteq)$  be a complete lattice and  $\Phi : D \rightarrow D$  continuous. Then:

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

### Corollary: upper bounds on weakest pre-expectations

For  $\text{while}(\varphi)\{P\}$  and expectations  $f$  and  $l$  we have:

$$\underbrace{\Phi_f(l) \sqsubseteq l}_{\text{wp-superinvariant}} \quad \text{implies} \quad \underbrace{wp[\text{while}(\varphi)\{P\}](f) \sqsubseteq l}_{\text{lfp } \Phi_f}$$

## Example

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

Claim:  $l = x + [c = 0] \cdot \frac{p}{1-p}$  is a super-invariant of  $P$  w.r.t.  $f = x$ .

## Proof

## Verifying loops

The following procedure for induction (and co-induction):

1. Guess 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  $\Phi(I) \sqsubseteq I$ , for induction (upper bound to wp), or
  - 3.2  $I \sqsubseteq \Psi(I)$ , for co-induction (lower bound to wlp).

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

## Induction for lower bounds **on wlp**

Recall:

$$\text{wlp}[\text{while}(\varphi)\{P\}](f) = \text{gfp } X. \underbrace{([\varphi] \cdot \text{wlp}[P](X) + [\neg\varphi] \cdot f)}_{\Psi_f(X)}$$

Park's lemma: let  $(D, \sqsubseteq)$  be a complete lattice and  $\Psi : D \rightarrow D$  continuous. Then:

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

### Corollary: lower bounds on weakest liberal pre-expectations

For  $\text{while}(\varphi)\{P\}$  and bounded expectations  $f$  and  $I$  we have:

$$\underbrace{I \sqsubseteq \Psi_f(I)}_{\text{wlp-subinvariant}} \quad \text{implies} \quad I \sqsubseteq \underbrace{\text{wlp}[\text{while}(\varphi)\{P\}](f)}_{\text{gfp } \Psi_f}$$

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## Aiming for lower bounds on wp (= lfp)

The following result does **not** hold:

$$I \sqsubseteq \Phi_f(I) \text{ implies } I \sqsubseteq \text{lfp } \Phi_f$$

Pictorially:

## Conclusion

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

$$\forall d \in D. \ d \sqsubseteq \Phi(d) \text{ does not imply } d \sqsubseteq \text{lfp } \Phi.$$

Co-induction for lower bounds on wp of loops is **unsound**.

Induction on upper bounds on wlp of loops also **fails**:

$$\forall d \in D. \ \Phi(d) \sqsubseteq d \text{ does not imply } \text{gfp } \Phi \sqsubseteq d.$$

Induction for upper bounds on wlp of loops is **unsound**.

## Counterexample

## A proof rule for lower bounds on wp

### Proof rule for lower bounds

$$(I \sqsubseteq \Phi_f(I) \wedge \text{side conditions}) \text{ implies } I \sqsubseteq \text{lfp } \Phi_f$$

where the side conditions for pGCL program  $\text{while}(\varphi)\{P\}$  are:

1.  $\text{while}(\varphi)\{P\}$  terminates in finite expected time, and
2. for any  $s \models \varphi$ ,  $\underbrace{\text{wp}[[P]](|I(s) - I|)(s)}_{\text{conditional difference boundedness}} \leq c$  for some given  $c \in \mathbb{R}_{\geq 0}$ .

## Example

## Proof

## A simpler proof rule for lower bounds

### Guard strengthening for lower bounds

Let  $P_{loop} = \text{while}(\varphi)\{P\}$  and  $P'_{loop} = \text{while}(\varphi')\{P\}$ , and expectations  $f$  and  $l$ . Then it holds:

$$(\varphi' \Rightarrow \varphi \wedge l \sqsubseteq \underbrace{wp[[P'_{loop}]]([\neg\varphi] \cdot f)}_{\text{lfp } \Phi'_{[\neg\varphi] \cdot f}}) \text{ implies } l \sqsubseteq \underbrace{wp[[P_{loop}]](f)}_{\text{lfp } \Phi_f}$$

- ▶ This rule is more general (e.g., applicable to divergent loops)
- ▶ The tightness of the lower bound depends on  $\varphi'$  approximating  $\varphi$
- ▶ Algorithmically in case  $P'_{loop}$  has finitely many states

## Random walks

Let  $\oplus$  abbreviate a uniform distribution. 1D-symmetric random walk on  $\mathbb{Z}$ :

$$\text{while } (x \neq 0) \{ x := x+1 \oplus x := x-1 \}$$

2D-symmetric random walk on  $\mathbb{Z}^2$ :

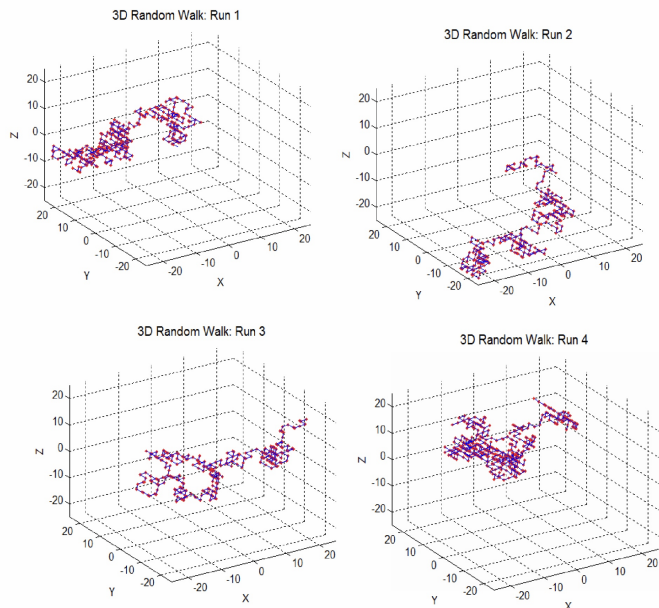
$$\text{while } (x \neq 0 \vee y \neq 0) \{ \\ x := x+1 \oplus x := x-1 \oplus y := y+1 \oplus y := y-1 \}$$

3D-symmetric random walk on  $\mathbb{Z}^3$ :

$$\text{while } (x \neq 0 \vee y \neq 0 \vee z \neq 0) \{ \\ x := x+1 \oplus x := x-1 \oplus \\ y := y+1 \oplus y := y-1 \oplus \\ z := z+1 \oplus z := z-1 \}$$

The 1D and 2D random walks reach the origin with probability one.  
The 3D random walks does not.

### Example: 3D symmetric random walk on $\mathbb{Z}^3$



### Pólya's analysis result

The termination probability of the 3D symmetric random walk starting from any neighbour location of the origin  $(0,0,0)$  equals

$$1 - \left( \frac{3}{(2\pi)^3} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} \frac{dx dy dz}{3 - \cos x - \cos y - \cos z} \right)^{-1} = 0.3405373296\dots$$

Can we obtain a **tight lower bound** on the termination probability?

### Example: 3D symmetric random walk on $\mathbb{Z}^3$



George Pólya (1887-1985)

### Obtaining a lower bound

```
while (x ≠ 0 ∨ y ≠ 0 ∨ z ≠ 0) {
  x := x+1 ⊕ x := x-1 ⊕
  y := y+1 ⊕ y := y-1 ⊕
  z := z+1 ⊕ z := z-1 }
```

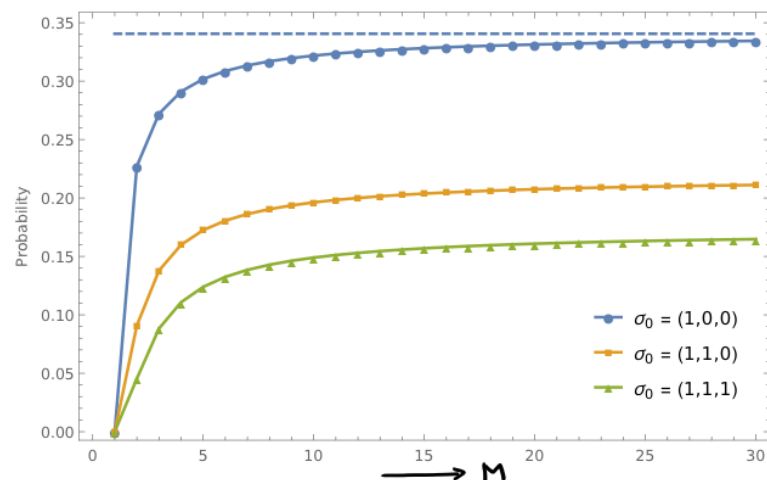
Bound the positions  $(x, y, z)$  to a cube of side length  $2 \cdot M$  for  $M \in \mathbb{N}_{>0}$ :

```
while ((x ≠ 0 ∨ y ≠ 0 ∨ z ≠ 0) ∧ |x| ≤ M ∧ |y| ≤ M ∧ |z| ≤ M) {
  x := x+1 ⊕ x := x-1 ⊕
  y := y+1 ⊕ y := y-1 ⊕
  z := z+1 ⊕ z := z-1 }
```

As the resulting program  $P'$  is finite state,  $wp[[P']](1)$  can be computed algorithmically. By increasing  $M$ , we approximate Pólya's result arbitrarily closely.



## Verification results



## 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
}

```

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## An alternative program

```

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
}

```

## Program equivalence: $X - Y$

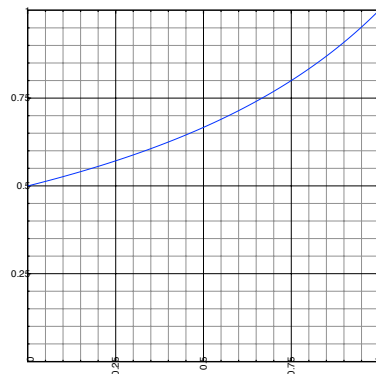
```
int XminY1(float p, q){
  int x, c := 0, 1;
  while (c) {
    (x += 1 [p] c := 0);
  }
  c := 1;
  while (c) {
    (x -= 1 [q] c := 0);
  }
  return x;
}
```

```
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;
}
```

For which  $p$  and  $q$  are the expected outcomes for  $f = x$  equal?

## Program equivalence

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;
}
```

```
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;
}
```

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

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

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

## Take-home messages

- ▶ Loop invariants allow to reason about (unbounded) loops
- ▶ Probabilistic invariants are expectations
- ▶ That either are lower or upper bounds of loops
- ▶ Upper bounds can be obtained by Park's lemma
- ▶ Lower bounds can be obtained by strengthening the loop guard
- ▶ Or by difference bounded loop bodies and finite termination

Next lecture: conditioning

## Next lecture

Thursday Nov 24, 16:30