# **Probabilistic Programming** Lecture #16+#17: Expected Runtime Analysis



Joost-Pieter Katoen

### RWTH Lecture Series on Probabilistic Programming 2018

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Overview		
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2 An unsound approach		
3 The expected runtime transfor	mer	
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6 Proving positive almost-sure te	ermination	
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### Probabilistic Programming

### Overview



- 2 An unsound approach
- 3 The expected runtime transformer
- Properties
- **(5)** Proof rules for runtimes of loops
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## Probabilistic Programming

Probabilistic Programming

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Motivation

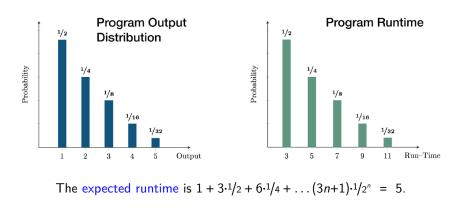
### The runtime of a probabilistic program

The runtime of a probabilistic program depends on the input and on the internal randomness of the program.

Motivation

### The runtime of a probabilistic program is random

```
int i := 0;
repeat {i++; (c := false [0.5] c := true)}
until (c)
```

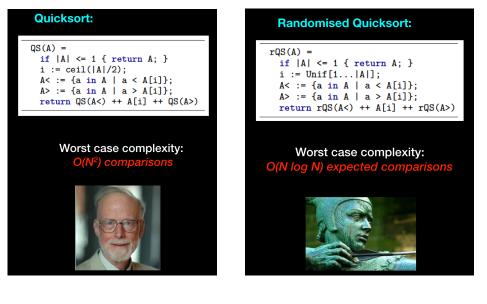


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#### Probabilistic Programming

Motivation

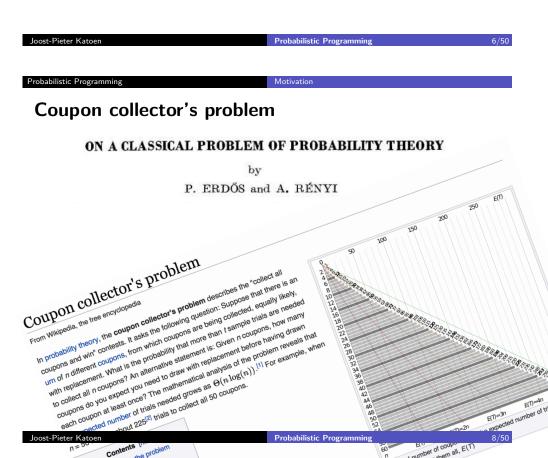
### Efficiency of randomised algorithms



### Expected runtimes

Expected run-time of program P on input s:

 $\sum_{i=1}^{\infty} i \cdot Pr \left( \begin{array}{c} "P \text{ terminates after} \\ i \text{ steps on input } s" \end{array} \right)$ 



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#### Motivat

### Coupon collector's problem

cp := [0,...,0]; // no coupons yet i := 1; // coupon to be collected next x := 0: // number of coupons collected while (x < N) { while (cp[i] != 0) { i := uniform(1..N) // next coupon } cp[i] := 1; // coupon i obtained x++; // one coupon less to go }

The expected runtime of this program is in  $\Theta(N \cdot \log N)$ .

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Probabilistic Programming	Motivation	
Randomised primality test		

### Problem: is *N* prime or not?

Basic structure of a randomised primality test:

- 1. Randomly pick a number a, say
- 2. Do the primality test: Check some equality involving a and N
- 3. If equality fails, N is composite (with witness a)
- 4. Otherwise repeat the process.

If after K > 0 iterations, N is not found to be composite, then N is probably prime.

### Closest-pair problem



Closest-pair problem: find two distinct points  $u, v \in \mathbb{R}^2$  among N points in the plane that minimise the Euclidean distance among all pairs of these points.

A naive deterministic approach takes  $O(N^2)$ . More efficient version in  $O(N \cdot \log N)$ .

Rabin's randomised algorithm has an expected runtime in O(N).

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### Some primality tests

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► Fermat primality test:

Select  $a \in \mathbb{Z}$  relative prime to N. If  $a^{N-1} \mod N \neq 1$ , then N is composite.

- ▶ Rabin-Miller test: Select 0 < a < N. Let  $2^s \cdot d = N-1$  where *d* is odd. If  $a^d \neq 1 \pmod{N}$  and  $a^{2^r \cdot d} \neq -1 \pmod{N}$  for all  $0 \le r \le s-1$ , then *N* is composite.
- Solovay and Strassen test: For N odd, pick a < N. If  $a^{N-1/2} \neq \dots$ , then N is composite.

Adleman and Huang (1992) provided a randomised primality test that terminates with expected polynomial runtime and certainly provides the correct answer.  $^1$ 

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<sup>&</sup>lt;sup>1</sup>Decision problems with this characteristic constitute the complexity class ZPP (zero-error probabilistic polynomial time).

#### Motivation

### The aim of this lecture

A wp-calculus to reason about runtimes at the source code level. No "descend" into the underlying probabilistic model. The calculus should be compositional. Proving positive almost-sure termination

- What? AST+termination in finite expected time
- ► Generalise. How?
  - Provide an weakest-precondition calculus
  - ..... for expected runtimes

### ► Why?

- Reason about the efficiency of randomised algorithms
- Reason about simulation efficiency of Bayesian networks
- Is compositional and reasons at the program's code

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Probabilistic Programming	Motivation		
Hurdles in runtime analysis			

1. Programs may admit diverging runs while still having a finite expected runtime

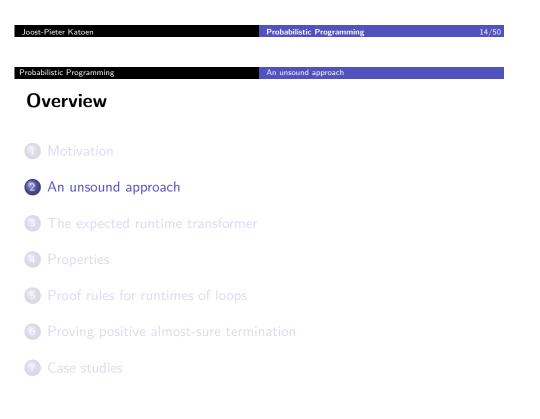
while  $(x > 0) \{ x-- [1/2] skip \}$ 

admits a diverging run but has expected runtime O(x).

- 2. Having a finite expected time is not compositional w.r.t. sequencing
- 3. Expected runtimes are extremely sensitive to variations in probabilities

while (x > 0) { x-- [1/2+p] x++ } // 0 <= p <= 1/2

- ▶ For *p*=0, the expected runtime is infinite.
- For arbitrary small p > 0, the expected runtime is  $1/2 \cdot p \cdot x$ , linear in x.



#### An unsound approach

### **Re-use weakest preconditions?**

Idea: equip the program with a counter rc and use standard wp-reasoning to determine its expected value.

Determine wp(P, rc) for program P.



Dexter Kozen A probabilistic PDL 1983

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Probabilistic Programming	An unsound approach
An example	
Consider t	he program <i>Q</i> :
x := 1; while (x > 0) { x := 0 [	[1/2] while(true) { skip } }

Equipping Q with a runtime counter yields  $Q_{rc}$ :

x := 1; rc := 0; while (x > 0) { rc++; (x := 0 [1/2] while(true) { rc++ ; skip}) }

As wp(inner loop, f) = 0 for every f, it follows  $\Phi_{Q_{rc}} \leq \Phi_{P_{rc}}$ . Thus,  $\Phi_{Q_{rc}}(I) \leq \Phi_{P_{rc}}(I) \leq I$  for  $I = rc + [x > 0] \cdot 2$ .

This contradicts the fact that the true expected runtime of Q is  $\infty$ .

### An example

An unsound approach

Consider the program P:

x := 1; while (x > 0) { x := 0 [1/2] skip }

Equipping $P$ with a runtime counter yields $P_{rc}$ :
<pre>x := 1; rc := 0; while (x &gt; 0) { rc++; (x := 0 [1/2] skip) }</pre>
It follows $\Phi(I) \leq I$ for $I = rc + [x > 0] \cdot 2$ .
In total, we thus obtain $wp(P_{rc}, rc) = 2$ .

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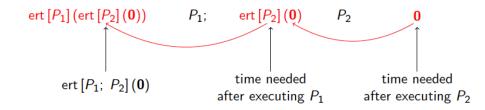
```
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```

#### The expected runtime transformer

### The basic idea

Let  $ert() : pGCL \to (\mathbb{T} \to \mathbb{T})$  where:

- ert(P, t)(s) is the expected runtime of P on input state s if t captures the runtime of the computation following P.
- $ert(P, \mathbf{0})(s)$  is the expected runtime of P on input state s.



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Probabilistic Programming	The expected runtime transformer
The runtime model	

We assume the following runtimes:

- Executing a skip-statement takes a single time unit
- Executing an (ordinary or random) assignment takes a single time unit
- Evaluating a guard takes a single time unit
- ▶ Flipping a coin in a probabilistic choice takes a single time unit
- Sequential composition does not take time

The ert-calculus can be easily adapted to other runtime models.

### Runtimes

### Expectations

A expectation  $f : \mathbb{S} \to \mathbb{R}_{\geq 0} \cup \{\infty\}$ .

Let  $\mathbb{E}$  be the set of all expectations and let  $\sqsubseteq$  be defined for  $f, g \in \mathbb{E}$  by:

 $f \sqsubseteq g$  if and only if  $f(s) \le g(s)$  for all  $s \in \mathbb{S}$ .

### Runtimes

A runtime  $t : \mathbb{S} \to \mathbb{R}_{\geq 0} \cup \{\infty\}$ .

Let  $\mathbb{T}$  denote the set of all runtimes and let  $\leq$  be defined for  $t, u \in \mathbb{T}$  by:

 $t \le u$  if and only if  $t(s) \le u(s)$  for all  $s \in S$ .

A runtime transformer is defined in a similar way as an expectation transformer

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The expected runtime transforme

## Expected runtime transformer for pGCL

Syntax	<b>Expected runtime</b> <i>ert</i> ( <i>P</i> , <i>t</i> )
▶ skip	▶ 1+ <i>t</i>
<ul><li>diverge</li></ul>	▶ ∞
▶ x := E	$1 + t[x \coloneqq E]$
▶ x :r= mu	► 1 + $\lambda s. \int_{\mathbb{O}} (\lambda v. t(s[x \coloneqq v])) d\mu_s$
▶ P1 ; P2	$ rt(P_1, ert(P_2, t)) $
▶ if (G)P1 else P2	▶ $1 + [G] \cdot ert(P_1, t) + [\neg G] \cdot ert(P_2, t)$
▶ P1 [p] P2	▶ $1 + p \cdot ert(P_1, t) + (1-p) \cdot ert(P_2, t)$
while(G)P	▶ Ifp X. $(1 + [G] \cdot ert(P, X) + [\neg G] \cdot t)$

If p is the least fixed point operator wrt. the ordering  $\leq$  on runtimes

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#### The expected runtime transformer

### Examples

#### Probabilistic Programming

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- **5** Proof rules for runtimes of loops
- 6 Proving positive almost-sure termination
- Case studies

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Probabilistic Programming	Properties
Elementary properties	
Continuity:	$ert(P, t)$ is continuous on $(\mathbb{T}, \leq)$
Monotonicity:	$t \le t'$ implies $ert(P, t) \le ert(P, t')$
Constant propagation:	$ert(P, \mathbf{k} + t) = \mathbf{k} + ert(P, t)$
• Preservation of $\infty$ :	$ert(P,\infty) = \infty$
Connection to wp:	ert(P, t) = ert(P, 0) + wp(P, t)
• Affinity: $ert(P, a \cdot t + t)$	') = $ert(P, 0) + r \cdot ert(P, t) + ert(P, t')$

J	loost-Pieter Katoen	Proba	bilistic Programming	26/50
Ρ	robabilistic Programming	Prope	rties	
	(Positivo) almost sure	tormin	ation	
	(Positive) almost-sure	termina		
	For every pGCL program $P$ and i	pput stat		
	For every poch program F and i	nput state	2 5.	
	$ert(P, 0)(s) < \infty$	implies	wp(P, 1)(s) = 1	
	positive a.s-termination on s		wp(P, 1)(s) = 1 almost-sure termination on s	
	Moreover:			
	$ert(P, 0) \leq \infty$	implies	wp(P, 1) = 1	
	universal positive a.s-termination			

### A Markov chain perspective on runtimes

- ► Consider *ert*(*P*, *t*) for pCGL program *P*
- Consider the Markov chain [[ P ]] of program P
- Attach rewards to each Markov chain state in [[ P ]]:
  - State  $\langle \downarrow, s \rangle$  gets reward t(s)
  - State (skip, s) gets reward one
  - ▶ State (diverge, s) gets reward ∞
  - State  $\langle x := E, s \rangle$  gets reward one
  - State  $\langle x :\approx \mu, s \rangle$  gets reward one
  - State (if  $G \dots, s$ ) gets reward one
  - State  $\langle P[p]Q, s \rangle$  gets reward one
  - State (while(G)P'..., s) gets reward one
  - All other states get reward zero

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Probabilistic Programming	Properties

Correspondence between *ert()* and Markov chains

### **Compatibility theorem**

For every pGCL program P and input s:

$$ert(P, \mathbf{0})(s) = ER^{\llbracket P \rrbracket}(s, \diamondsuit sink)$$

In words: the  $ert(P, \mathbf{0})$  for input *s* equals the expected reward to reach final state *sink* in MC [[ *P* ]] where reward function *r* in [[ *P* ]] is defined as defined on the previous slide.

Example

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 Properties

 Backward compatibility

### **Deterministic programs**

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For any GCL program P,  $ert(P, \mathbf{0})$  equals the number of executed computational steps<sup>2</sup> of P until P terminates.

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<sup>&</sup>lt;sup>2</sup>This equals the number of skip statements, guard evaluations and assignments.

robabilistic Programming Proof rules for runtimes of loops	Probabilistic Programming Proof rules for r
Overview	Loops
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### **Runtime invariants**

### Runtime invariants

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Let  $\Phi_t$  be the wp-characteristic function of  $P' = \text{while}(G)\{P\}$  with respect to post-runtime  $t \in \mathbb{T}$  and let  $l \in \mathbb{T}$ . Then:

- 1. *I* is a runtime-superinvariant of P' w.r.t. *t* iff  $\Phi_t(I) \leq I$ .
- 2. *I* is a runtime-subinvariant of *P*' w.r.t. *t* iff  $I \leq \Phi_t(I)$ .

If *I* is a runtime-superinvariant of while (G) with respect to  $t \in \mathbb{T}$ , then:

 $ert(while(G)\{P\}, t) \leq I$ 

for wp — invariants.

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Probabilistic Programming	Proof rules for runtimes of loops	
Example		

Example

Proof rules for runtimes of loops

#### Proof rules for runtimes of loops

### A wrong proof rule for lower bonds

### Probabilistic programs do not satisfy:

if  $l \leq \Phi_t(l)$  then  $l \leq ert(while(G) P, t)$ .

These "metering" functions / do work for ordinary programs

[Frohn et al., IJCAR 2016]



### A counterexample

while (true) { skip [1/2] x++ }

- Characteristic functional  $F(X) = \mathbf{1} + \frac{1}{2}(\mathbf{1} + \mathbf{1} + X[x/x+1])$
- Least fixed point is 4 as  $F(4) = 2 + \frac{1}{2} \cdot 4 = 4$
- $4 + 2^i$  is a fixed point of F too:

$$F(4+2^{i}) = 2 + \frac{1}{2}(4+2^{i+1}) = 4+2^{i}$$

Thus: 4 + 2<sup>i</sup> ≤ F(4 + 2<sup>i</sup>) but 4 + 2<sup>i</sup> ≰ 4 = lfp F
In fact, 4 + 2<sup>i+c</sup> is a fixed point of F for any c:

$$F(4+2^{i+c}) = 2 + \frac{1}{2}(4+2^{i+c+1}) = 4+2^{i+c}$$

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Probabilistic Programming	Proof rules for runtimes of loops	
Runtime $\omega$ -invariants		

### **Runtime** $\omega$ -invariants

Let  $n \in \mathbb{N}$ ,  $t \in \mathbb{T}$  and  $\Phi_t$  the ert-characteristic function of while(G){P}. The monotonically increasing<sup>3</sup> sequence  $(I)_{n \in \mathbb{N}}$  is a runtime- $\omega$ -subinvariant of the loop w.r.t. runtime t iff

 $I_0 \leq \Phi_t(\mathbf{0})$  and  $I_{n+1} \leq \Phi_t(I_n)$  for all n.

In a similar way, runtime  $\omega$ -superinvariants can be defined, but we will not use them here.

### **Runtime lower bounds**

If  $I_n$  is a runtime  $\omega$ -subinvariant of while(G){P} with respect to t, then:

 $\sup_{n} I_{n} \leq ert(while(G) P, t)$ 

### Example

Consider the same program as for proving an upper bound on the expected runtime.

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<sup>&</sup>lt;sup>3</sup>But not necessarily strictly increasing.

robabilistic Programming Overview	Proving positive almost-sure termination	Probabilistic Programming PAST is not con
1 Motivation		Cor
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3 The expected runtime transforme	er	<pre>int x := 1; bool c := true; while (c) {</pre>
4 Properties		c := <b>false</b>   x := 2*x
5 Proof rules for runtimes of loops		} Finite expected t
6 Proving positive almost-sure tern	mination	
7 Case studies		Rur yield:

Proving positive almost-sure termination

Proving that PAST is not compositional (1)

It is easy to check that a lower  $\omega$ -invariant is:

 $J_n = \mathbf{1} + [0 < x < n] \cdot 2x + [x \ge n] \cdot (2n-1)$ on iteration on termination

Thus we obtain that:

$$\lim_{n \to \infty} \left( \mathbf{1} + [0 < x < n] \cdot 2x + [x \ge n] \cdot (2n-1) \right) = \mathbf{1} + [x > 0] \cdot 2x$$

is a lower bound on the runtime of the above program.

### ompositional

onsider the two probabilistic programs:

<pre>int x := 1;</pre>
<pre>bool c := true;</pre>
<pre>while (c) {</pre>
c := <b>false</b> [0.5] c := <b>true</b> ;
x := 2*x
}

while (x > 0) { x--}

termination time

Finite termination time

unning the right after the left program ds an infinite expected termination time

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Proving positive almost-sure termination

Proving that PAST is not compositional (2)

while (c) { {c := false [0.5] c := true}; x := 2\*x}; while  $(x > 0) \{ x := x-1 \}$ 

Template for a lower  $\omega$ -invariant of composed program:

$$I_n = \mathbf{1} + \underbrace{[c \neq 1] \cdot (\mathbf{1} + [x > 0] \cdot 2x)}_{\text{on termination}} + \underbrace{[c = 1] \cdot (a_n + b_n \cdot [x > 0] \cdot 2x)}_{\text{on iteration}}$$

The constraints on being a lower  $\omega$ -invariant yield:

 $a_0 \le 2$  and  $a_{n+1} \le 7/2 + 1/2 \cdot a_n$  and  $b_0 \le 0$  and  $b_{n+1} \le 1 + b_n$ 

This admits the solution  $a_n = 7 - 5/2^n$  and  $b_n = n$ . Then:  $\lim_{n \to \infty} I_n = \infty$ .

#### Proving positive almost-sure termination

### Proving PAST

The ert-transformer enables to prove that a program is positively almost-surely terminating in a compositional manner,

although PAST itself is not a compositional property.

#### obabilistic Programmin

### Overview

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Case studies

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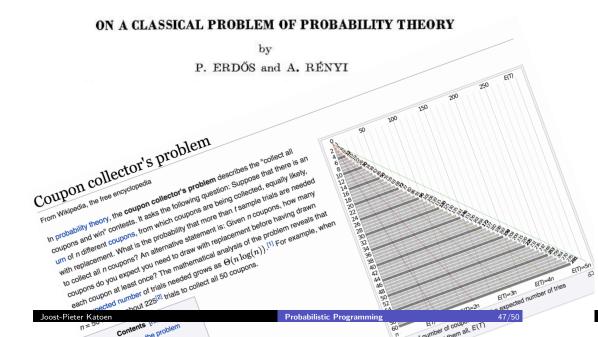
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Case studies

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### **Coupon collector's problem**



### **Coupon collector's problem**

```
cp := [0,...,0]; i := 1; x := 0; // no coupons yet
while (x < N) {
  while (cp[i] != 0) {
      i := uniform(1..N) // next coupon
  }
  cp[i] := 1; // coupon i obtained
  x++; // one coupon less to go
}
```

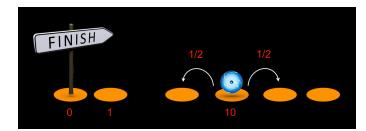
Using the ert-calculus one can prove that:

 $ert(cpcl, \mathbf{0}) = \mathbf{4} + [N > 0] \cdot 2N \cdot (2 + H_{N-1}) \in \Theta(N \cdot \log N)$ 

As Harmonic number  $H_{N-1} \in \Theta(\log N)$ . By systematic program verification. Machine checkable.

#### Case studies

### Random walk



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### Randomised binary search

```
proc BinSearch {
  mid := Unif(left, right); // pick mid uniformly
  if (left < right) {
      if (A[mid] < val) {
         left := min(mid+1, right);
         call BinSearch
      } else {
         if (A[mid] > val) {
            right := max(mid-1, left);
            call BinSearch
      } else { skip }
    }
}
```

Using the ert-calculus one can prove that its expected runtime is  $\infty$ .

By systematic formal verification. Machine checkable.

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Using the ert-calculus one can prove that its expected runtime is  $\Theta(\log N)$ .

By systematic formal verification. Machine checkable.

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