

# Tail Probabilities for Randomized Program Runtimes via Martingales for Higher Moments

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Ichiro Hasuo<sup>1,2</sup>

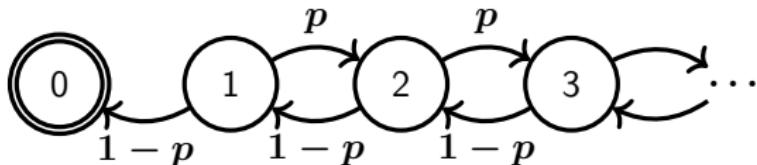
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# Our question

“What is an upper bound of the tail probability?”

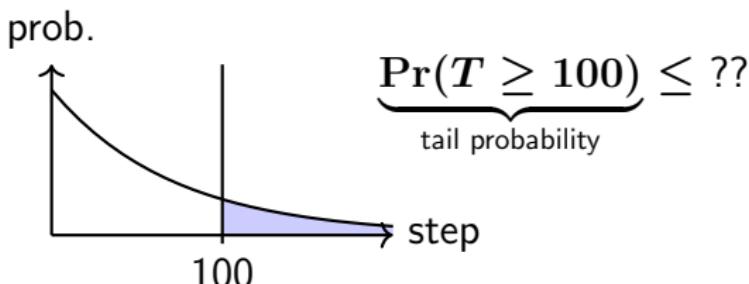


How likely is it to terminate within 100 steps?

(e.g. at least 90%)

How unlikely is it to not terminate within 100 steps?

(e.g. at most 10%)



# Related work

## Supermartingale-based approach

- Proving almost-sure termination  
[Chakarov & Sankaranarayanan, CAV'13]
- Overapproximating tail probabilities:

$$\Pr(T \geq d) \leq ??$$

[Chatterjee & Fu, arxiv preprint], [Chatterjee et al., TOPLAS'18]

- Azuma's, Hoeffding's and Bernstein's inequalities
- Markov's inequality (wider applicability)

$$\Pr(T \geq d) \leq \frac{\mathbf{E}[T]}{d}$$

# Our approach

- Aim: overapproximating tail probabilities:

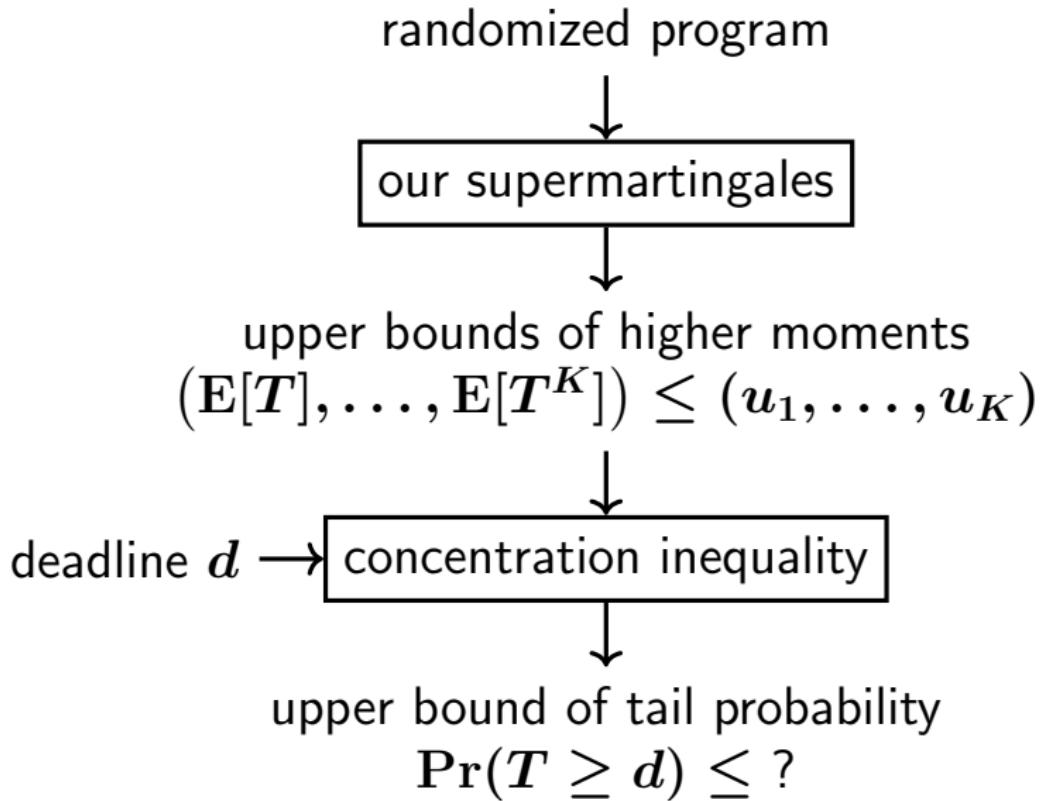
$$\Pr(T \geq d) \leq ??$$

- Corollary of Markov's inequality

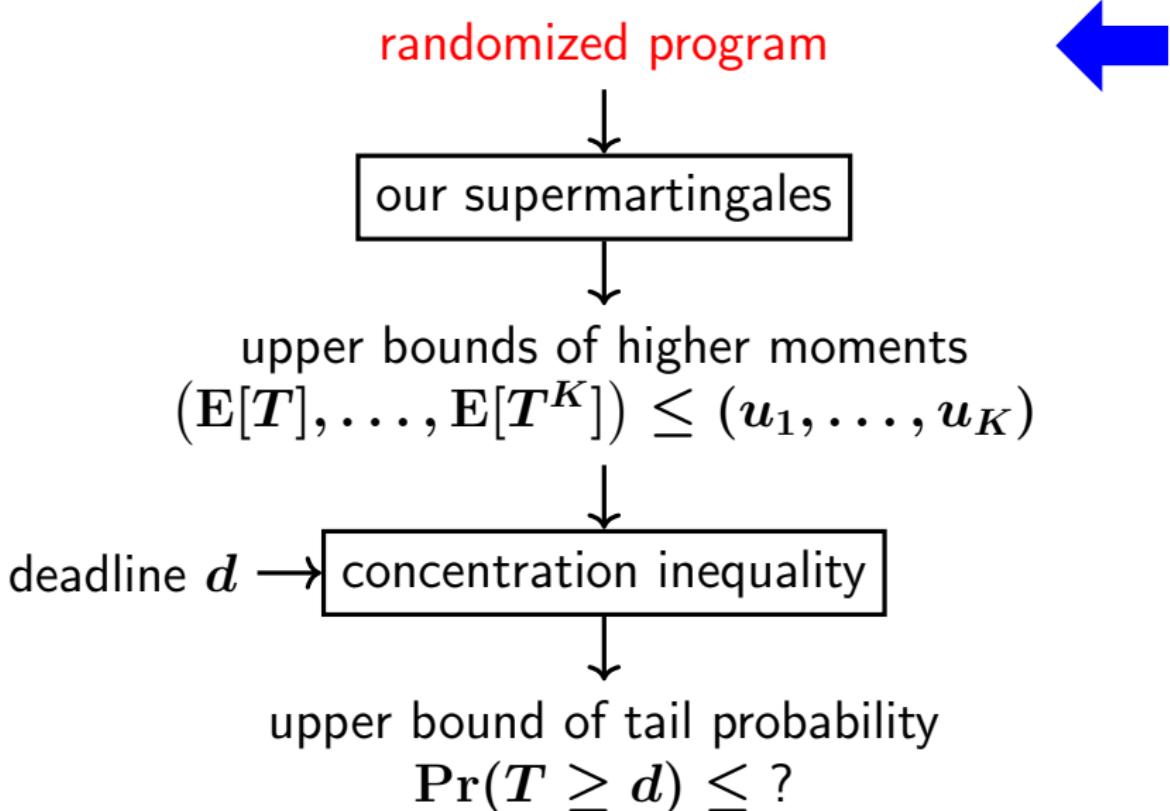
$$\Pr(T \geq d) \leq \frac{\mathbb{E}[T^k]}{d^k}$$

- Extends ranking supermartingale for  
higher moments  $\mathbb{E}[T^k]$  ( $k = 1, 2, \dots$ )

# Our workflow



# Our workflow

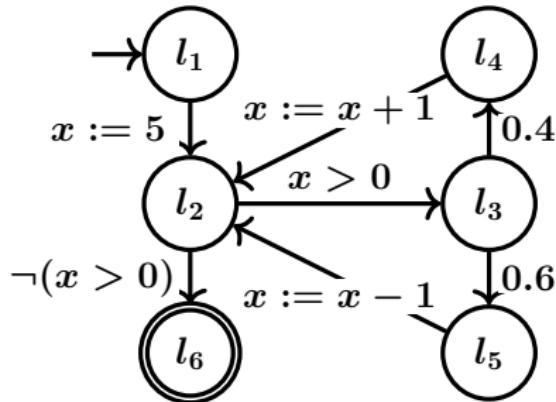


# Randomized program

- ✓ sampling
- ✓ (demonic/termination avoiding) nondeterminism

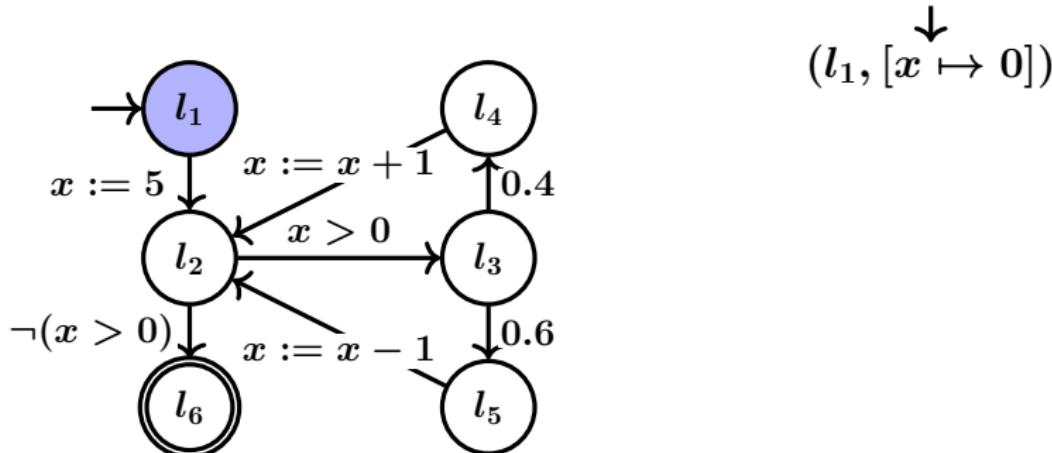
Given as a pCFG (probabilistic control flow graph).

```
1 x := 5;  
2 while x > 0 do  
3   if prob(0.4) then  
4     x := x + 1  
5   else  
6     x := x - 1  
7   fi  
8 od
```



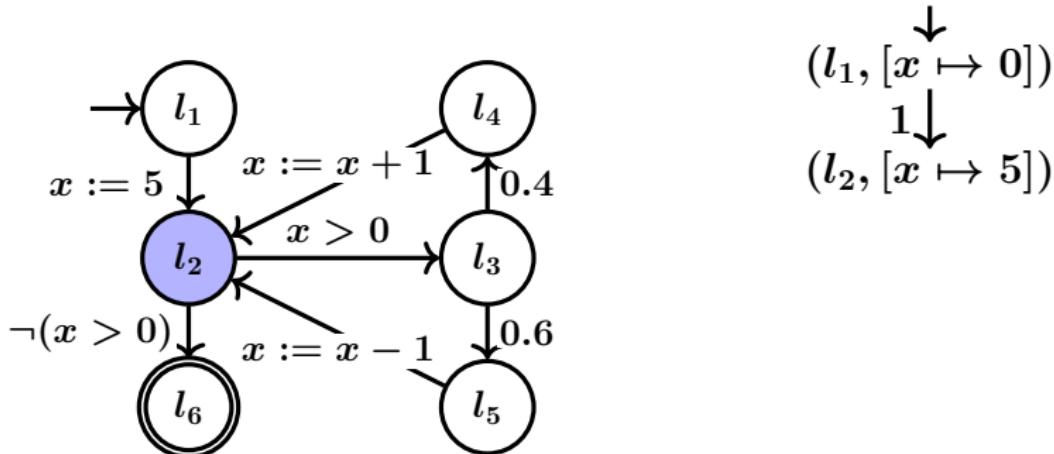
# Semantics

- Configuration:  $(l, \vec{x}) \in L \times \mathbb{R}^V$ 
  - $L$ : finite set of locations
  - $V$ : finite set of program variables
- Run: sequence of configurations



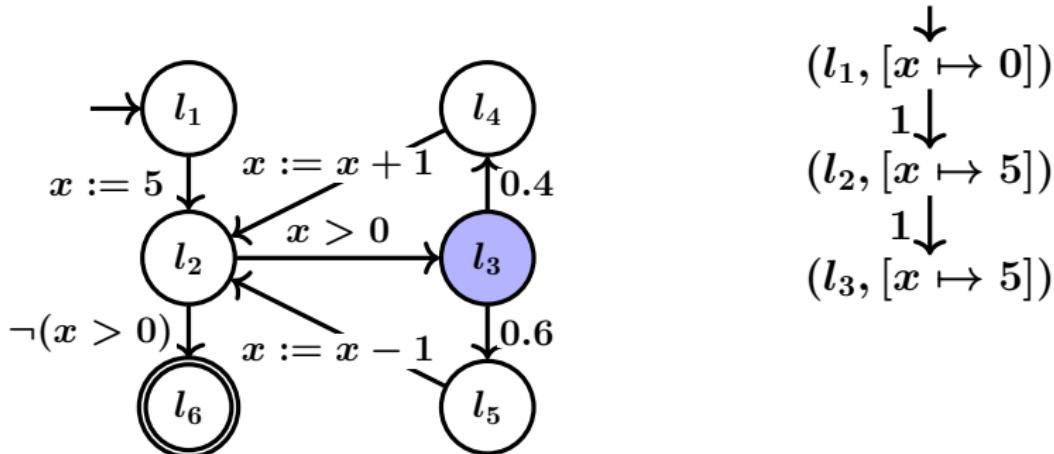
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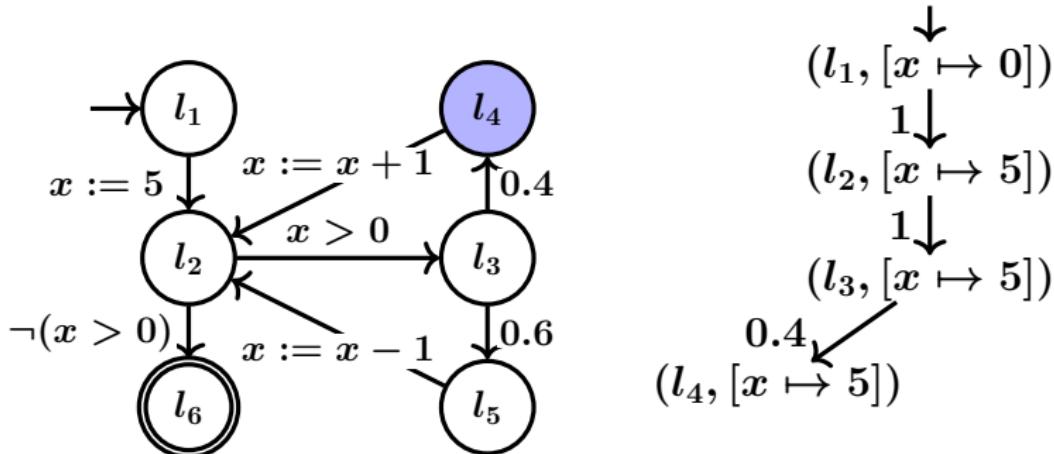
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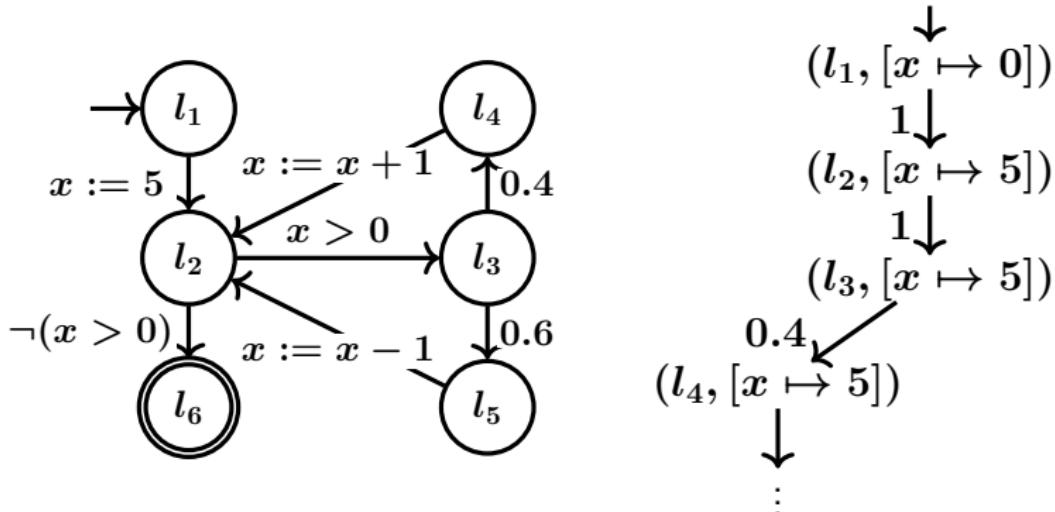
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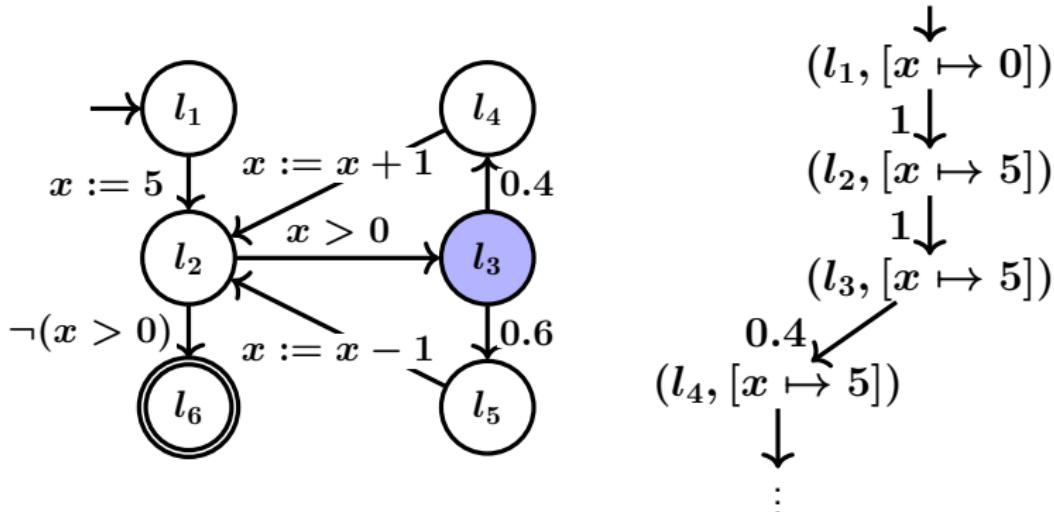
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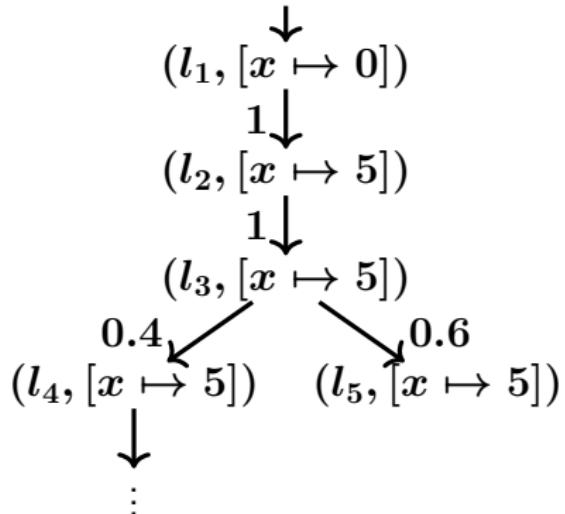
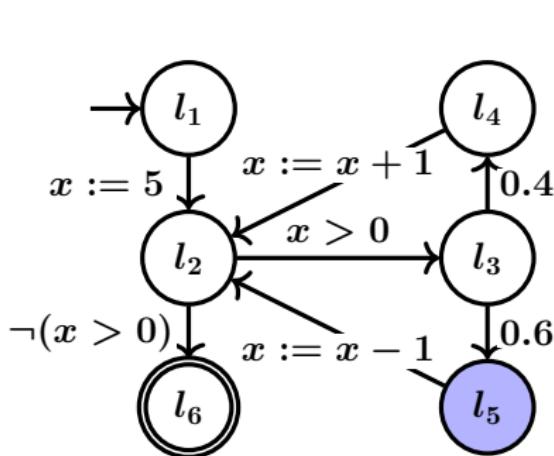
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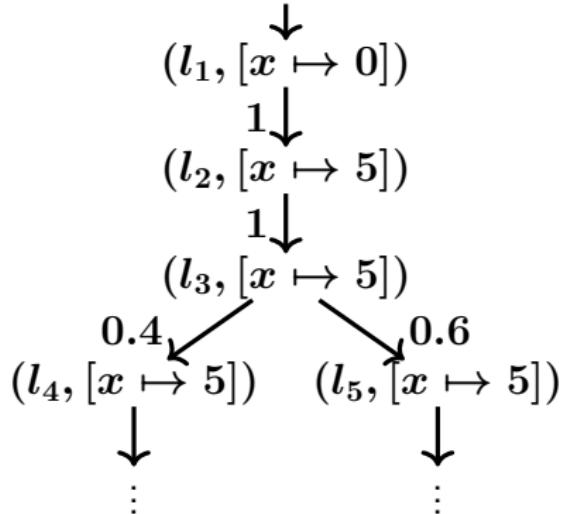
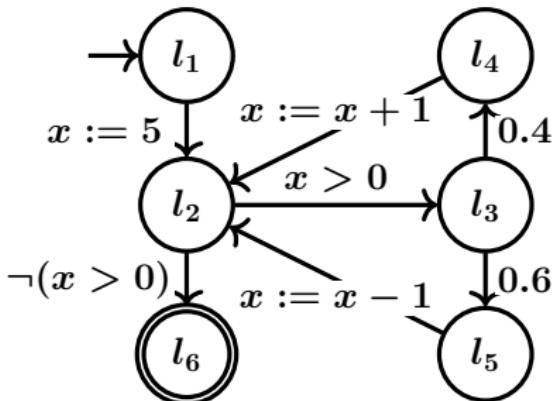
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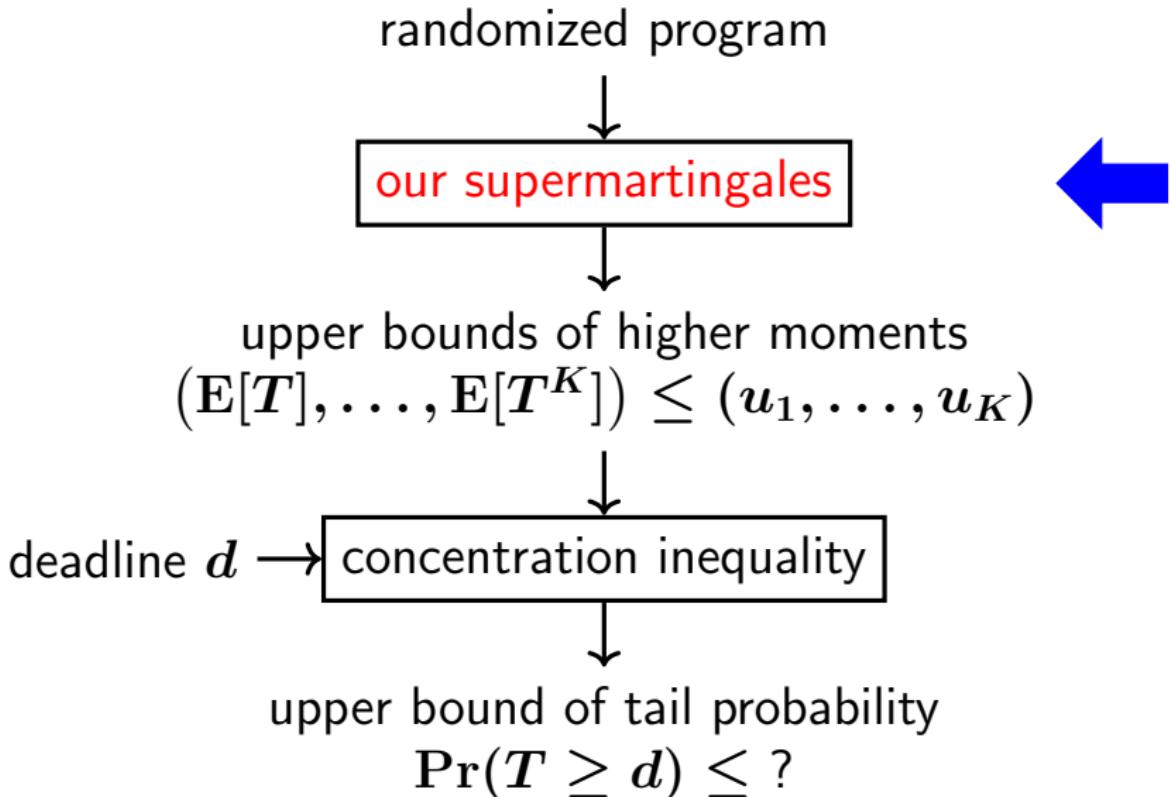


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- Run: sequence of configurations



# Our workflow



# Ranking function

[Floyd, '67]

$$r : L \times \mathbb{R}^V \rightarrow \mathbb{N} \cup \{\infty\}$$

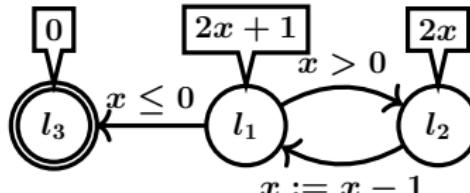
For each transition,  $r$  decreases by (at least) 1:

$$(l, \vec{x}) \mapsto (l', \vec{x}') \implies r(l', \vec{x}') \leq r(l, \vec{x}) - 1$$

## Theorem

If  $r(l, \vec{x}) < \infty$ , then the program is terminating from  $(l, \vec{x})$  within  $r(l, \vec{x})$  steps.

```
1   x := 5;  
2   while x > 0 do  
3       x := x - 1  
4   od
```



# Ranking supermartingale

[Chakarov & Sankaranarayanan, CAV'13]

$$\eta : L \times \mathbb{R}^V \rightarrow [0, \infty]$$

For each transition,  $\eta$  decreases by (at least) 1  
“on average”:

$$(\mathbb{X}\eta)(l, \vec{x}) \leq \eta(l, \vec{x}) - 1 \quad \text{for each } (l, \vec{x})$$

where  $\mathbb{X}$  is next-time operator (the expected value  
after one transition):

$$(\mathbb{X}\eta)(l, \vec{x}) := E[\eta(l', \vec{x}') \mid (l, \vec{x}) \mapsto (l', \vec{x}')].$$

# Ranking supermartingale

## Theorem

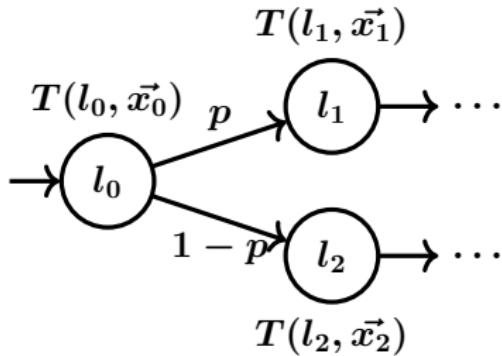
If  $\eta(l, \vec{x}) < \infty$ , then the program is (positively) almost surely terminating from  $(l, \vec{x})$  with the expected runtime  $\leq \eta(l, \vec{x})$  steps.

This can be explained lattice-theoretically.

- Expected runtime is a lfp
- Ranking supermartingale is a prefixed point

# Runtime before and after transition

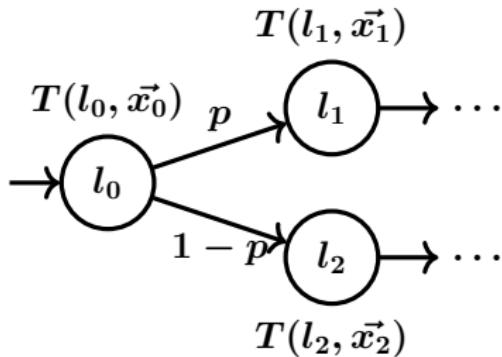
Let  $T(l, \vec{x})$  be a random variable representing the runtime from  $(l, \vec{x})$ .



Runtime from  $(l_0, \vec{x}_0)$ :

- $T(l_1, \vec{x}_1) + 1$  with probability  $p$
- $T(l_2, \vec{x}_2) + 1$  with probability  $1 - p$

# Expected runtime is a fixed point



$$\mathbb{E}[T](l_0, \vec{x}_0)$$

$$\begin{aligned} &= p\mathbb{E}[T(l_1, \vec{x}_1) + 1] + (1 - p)\mathbb{E}[T(l_2, \vec{x}_2) + 1] \\ &= p(\mathbb{E}[T(l_1, \vec{x}_1)] + 1) + (1 - p)(\mathbb{E}[T(l_2, \vec{x}_2)] + 1) \\ &= \mathbb{E} \left[ \mathbb{E}[T(l', \vec{x}')] + 1 \mid (l_0, \vec{x}_0) \mapsto (l', \vec{x}') \right] \\ &= (\mathbb{X}(\mathbb{E}[T] + 1))(l_0, \vec{x}_0) \end{aligned}$$

where  $\mathbb{E}[T] := \lambda(l, \vec{x}) \cdot \mathbb{E}[T(l, \vec{x})]$ .

## Expected runtime is Ifp

$$\mathbb{E}[T] = \mathbb{X}(\mathbb{E}[T] + 1)$$

In fact,  $\mathbb{E}[T]$  is the “least” fixed point of

$$F_1(\eta) := \mathbb{X}(\eta + 1).$$

- $F_1$  is a monotone function on the complete lattice  $[0, \infty]^{L \times \mathbb{R}^V}$
- $F_1$  adds 1 unit of time, and then calculate the expected value after one transition

# Ranking supermartingale is prefixed point

$\eta$  is a ranking supermartingale

$\iff \eta$  is a prefixed point of  $F_1$

$$F_1\eta = \mathbb{X}(\eta + 1) \leq \eta$$

## Theorem (Knaster–Tarski)

Let  $L$  be a complete lattice and  $F : L \rightarrow L$  be a monotone function. The least fixed point  $\mu F$  is the least prefixed point. Therefore we have

$$F\eta \leq \eta \implies \mu F \leq \eta.$$

It follows that

$$\eta \text{ is a ranking supermartingale} \implies \mathbb{E}[T] \leq \eta.$$

# Our supermartingale

	[Chakarov & Sankaranarayanan, CAV'13]
lattice	$L \times \mathbb{R}^V \rightarrow [0, \infty]$
monotone function $F$	$F_1$
lfp $\mu F$	$E[T]$
prefixed point $F\eta \leq \eta$	ranking supermartingale $\eta$
Knaster–Tarski $\mu F \leq \eta$	$E[T] \leq \eta$

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<sup>†</sup>for a pCFG without nondeterminism

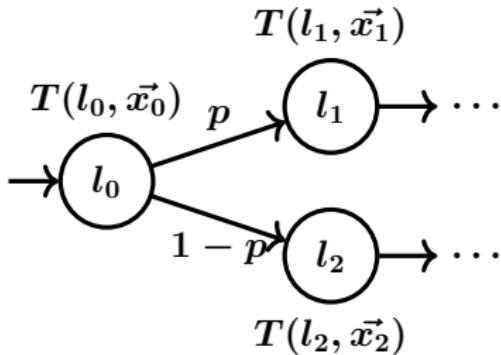
# Our supermartingale

	[Chakarov & Sankaranarayanan, CAV'13]	Our supermartingale
lattice	$L \times \mathbb{R}^V \rightarrow [0, \infty]$	$L \times \mathbb{R}^V \rightarrow [0, \infty]^K$
monotone function $F$	$F_1$	$F_K$
lfp $\mu F$	$E[T]$	$(E[T], \dots, E[T^K])^\dagger$
prefixed point $F\eta \leq \eta$	ranking supermartingale $\eta$	ranking supermartingale for <u>higher moments</u> $\vec{\eta}$
Knaster–Tarski $\mu F \leq \eta$	$E[T] \leq \eta$	$(E[T], \dots, E[T^K]) \leq \vec{\eta}$

<sup>†</sup>for a pCFG without nondeterminism

# Runtime before and after transition

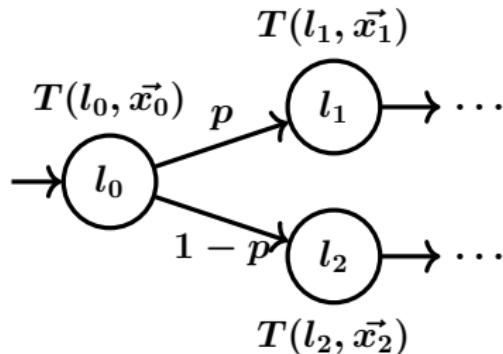
Let  $T(l, \vec{x})$  be a random variable representing the runtime from  $(l, \vec{x})$ .



Runtime from  $(l_0, \vec{x}_0)$ :

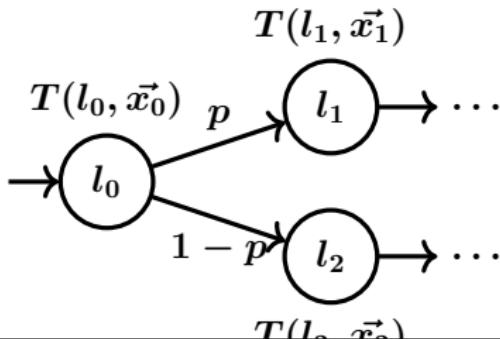
- $T(l_1, \vec{x}_1) + 1$  with probability  $p$
- $T(l_2, \vec{x}_2) + 1$  with probability  $1 - p$

# Characterizing $\mathbf{E}[T^2]$ as Ifp?



$$\begin{aligned}\mathbf{E}[T^2](l_0, \vec{x}_0) &= p\mathbf{E}[(T(l_1, \vec{x}_1) + 1)^2] \\ &\quad + (1 - p)\mathbf{E}[(T(l_2, \vec{x}_2) + 1)^2] \\ &= \left( \mathbb{X}(\mathbf{E}[T^2] + 2\underline{\mathbf{E}[T]} + 1) \right) (l_0, \vec{x}_0)\end{aligned}$$

# Characterizing $E[T^2]$ as Ifp?



Calculate  $E[T]$  and  $E[T^2]$  simultaneously

$$= \left( \mathbb{X}(E[T^2] + 2\underline{E[T]} + 1) \right) (l_0, \vec{x}_0)$$

# Characterizing $\mathbb{E}[T]$ and $\mathbb{E}[T^2]$ as lfp

$$\begin{pmatrix} \mathbb{E}[T] \\ \mathbb{E}[T^2] \end{pmatrix} = \mathbb{X} \left( \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} \mathbb{E}[T] \\ \mathbb{E}[T^2] \end{pmatrix} \right)$$

In fact,  $(\mathbb{E}[T], \mathbb{E}[T^2])$  is the “least” fixed point of

$$F_2 \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} := \mathbb{X} \left( \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} \right)$$

where

- $\eta_1, \eta_2 : L \times \mathbb{R}^V \rightarrow [0, \infty]$
- $\mathbb{E}[T] = \lambda(l, \vec{x}) \cdot \mathbb{E}[T(l, \vec{x})]$
- $\mathbb{E}[T^2] = \lambda(l, \vec{x}) \cdot \mathbb{E}[(T(l, \vec{x}))^2]$

# Characterizing higher moments as Ifp

In the same way, we can define

$$F_K : (L \times \mathbb{R}^V \rightarrow [0, \infty]^K) \rightarrow (L \times \mathbb{R}^V \rightarrow [0, \infty]^K)$$

that characterizes higher moments of runtime.

## Lemma

- For a pCFG without nondeterminism,

$$(\mathbf{E}[T], \dots, \mathbf{E}[T^K]) = \mu F_K.$$

- In general (with nondeterminism),

$$(\mathbf{E}[T], \dots, \mathbf{E}[T^K]) \leq \mu F_K.$$

# Supermartingale is a prefixed point

## Definition

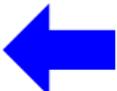
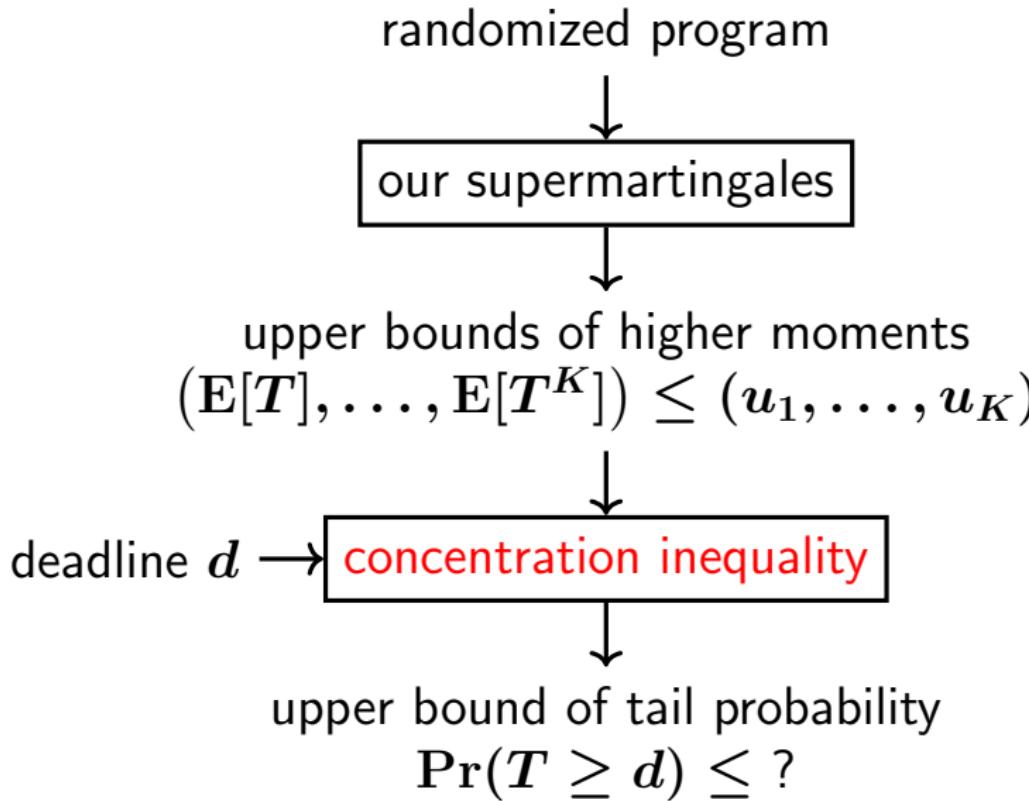
A **ranking supermartingale for  $K$ -th moment** is a prefixed point  $\vec{\eta} = (\eta_1, \dots, \eta_K)$  of  $F_K$ .

$$F_K \vec{\eta} \leq \vec{\eta}$$

By the Knaster–Tarski theorem,  $\vec{\eta}$  gives an upper bound (even with nondeterminism).

$$\begin{pmatrix} \mathbf{E}[T] \\ \vdots \\ \mathbf{E}[T^K] \end{pmatrix} \leq \mu F_K \leq \begin{pmatrix} \eta_1 \\ \vdots \\ \eta_K \end{pmatrix}$$

# Our workflow



# Problem

Assume

- $d > 0$ ,
- $T$  is a nonnegative random variable,
- $\begin{pmatrix} \mathbb{E}[T] \\ \vdots \\ \mathbb{E}[T^K] \end{pmatrix} \leq \begin{pmatrix} u_1 \\ \vdots \\ u_K \end{pmatrix}$ ,
- but we do not know the exact values of  $\mathbb{E}[T], \dots, \mathbb{E}[T^K]$ .

How to obtain an upper bound of  $P(T \geq d)$ ?

If  $K = 1 \dots$

Theorem (Markov's inequality)

If  $T$  is a nonnegative r.v. and  $d > 0$ ,

$$\Pr(T \geq d) \leq \frac{\mathbf{E}[T]}{d}.$$

By  $\mathbf{E}[T] \leq u_1$ ,

$$\Pr(T \geq d) \leq \frac{\mathbf{E}[T]}{d} \leq \frac{u_1}{d}.$$

## General case

- For any  $k \in \{1, \dots, K\}$ ,

$$\begin{aligned}\Pr(T \geq d) &= \Pr(T^k \geq d^k) \\ &\leq \frac{\mathbb{E}[T^k]}{d^k} \\ &\leq \frac{u_k}{d^k}\end{aligned}$$

- (“0-th” moment)

$$\Pr(T \geq d) \leq 1 = \frac{\mathbb{E}[T^0]}{d^0}$$

## Concentration inequality we used

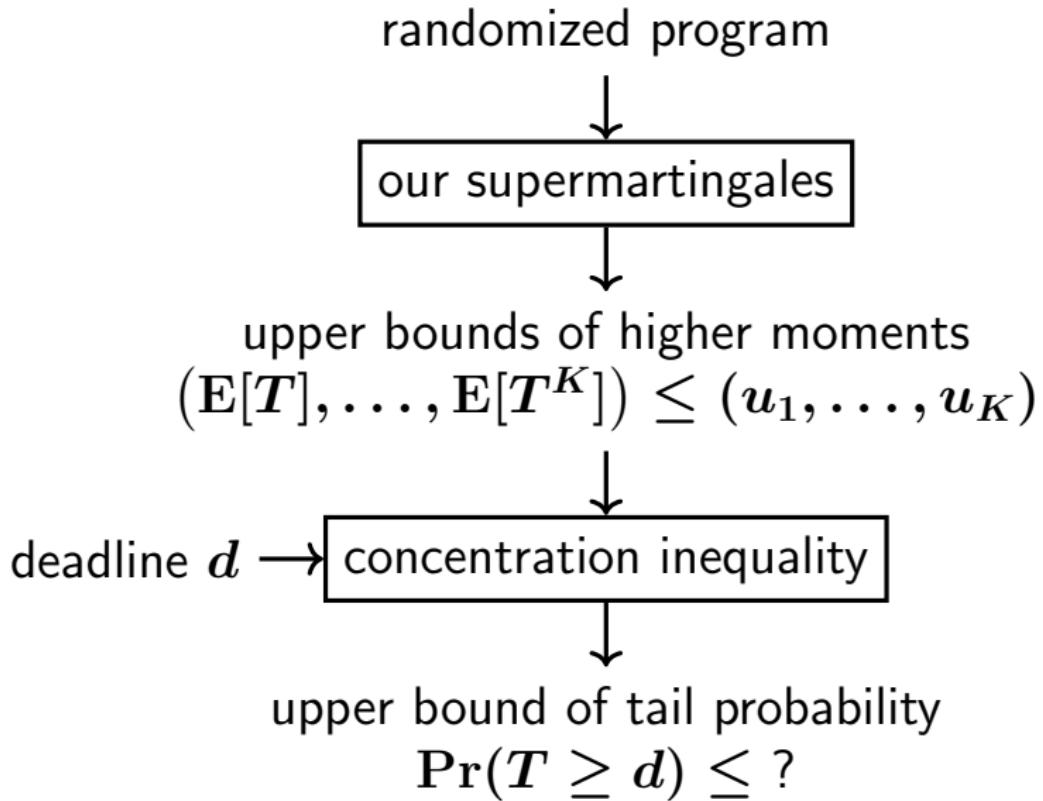
$$\Pr(T \geq d) \leq \min_{k=0,\dots,K} \frac{u_k}{d^k}$$

where

- $d > 0$
- $T$  is a nonnegative random variable
- $\begin{pmatrix} \mathbb{E}[T] \\ \vdots \\ \mathbb{E}[T^K] \end{pmatrix} \leq \begin{pmatrix} u_1 \\ \vdots \\ u_K \end{pmatrix}$
- $u_0 = 1$

Moreover, this gives the “optimal” upper bound under the above conditions.

# Our workflow



# Synthesis (linear template)

Based on [Chakarov & Sankaranarayanan, CAV'13]

- Input: a pCFG with initial config  $(l_{\text{init}}, \vec{x}_{\text{init}})$
- Output: an upper bound of  $\mathbf{E}[T^K](l_{\text{init}}, \vec{x}_{\text{init}})$

Assume that  $\vec{\eta} = (\eta_1, \dots, \eta_K)$  is linear:

$$\eta_k(l, \vec{x}) = \vec{a}_{k,l} \cdot \vec{x} + b_{k,l} \quad (k = 1, \dots, K)$$

Determine  $\vec{a}_{k,l}, b_{k,l}$  by solving the LP problem:

- minimize:  $\eta_K(l_{\text{init}}, \vec{x}_{\text{init}})$
- subject to: ranking supermartingale condition  
(using Farkas' lemma)

Then we have

$$\mathbf{E}[T^K](l_{\text{init}}, \vec{x}_{\text{init}}) \leq \min \eta_K(l_{\text{init}}, \vec{x}_{\text{init}})$$

# Synthesis (polynomial template)

Based on [Chatterjee et al., CAV'16]

- Input: a pCFG with initial config  $(l_{\text{init}}, \vec{x}_{\text{init}})$
- Output: an upper bound of  $\mathbf{E}[T^K](l_{\text{init}}, \vec{x}_{\text{init}})$

Assume that  $\vec{\eta} = (\eta_1, \dots, \eta_K)$  is polynomial.

Determine coefficients by solving the SDP problem:

- minimize:  $\eta_K(l_{\text{init}}, \vec{x}_{\text{init}})$
- subject to: ranking supermartingale condition  
(using Positivstellensatz)

Then we have

$$\mathbf{E}[T^K](l_{\text{init}}, \vec{x}_{\text{init}}) \leq \min \eta_K(l_{\text{init}}, \vec{x}_{\text{init}})$$

# Experiments

- Implementation based on linear/polynomial templates
- Tested 7 example programs
  - 2 coupon collector's problems
  - 5 random walks (some of them include nondeterminism)
- (degree of polynomial template)  $\leq 3$

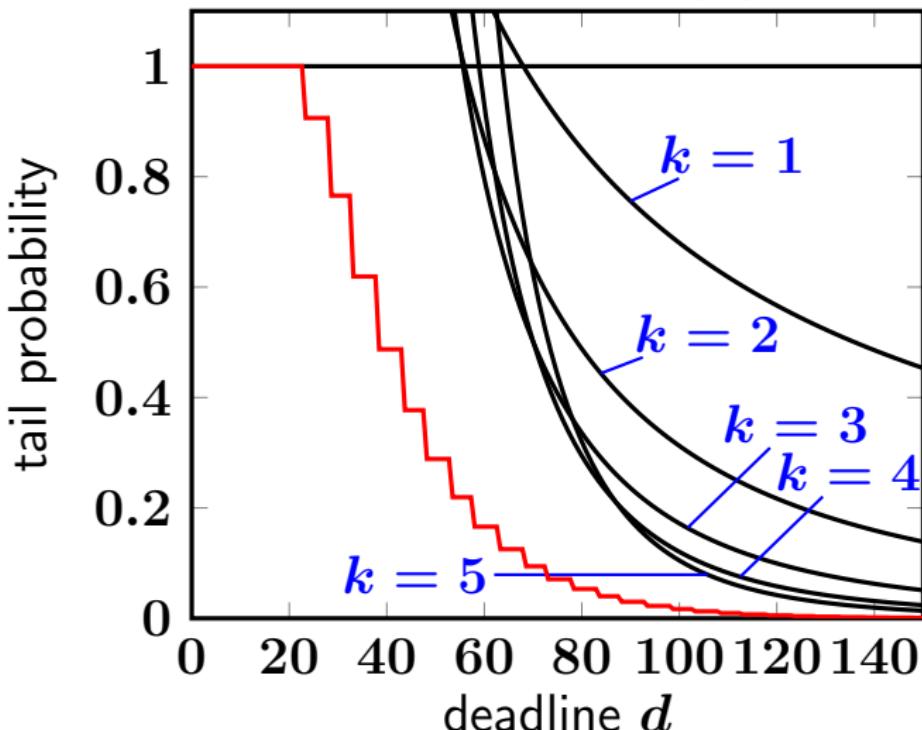
# Experimental result (1)

A coupon collector's problem (linear template)

upper bound	execution time
$E[T] \leq 68$	0.024 s
$E[T^2] \leq 3124$	0.054 s
$E[T^3] \leq 171932$	0.089 s
$E[T^4] \leq 12049876$	0.126 s
$E[T^5] \leq 1048131068$	0.191 s

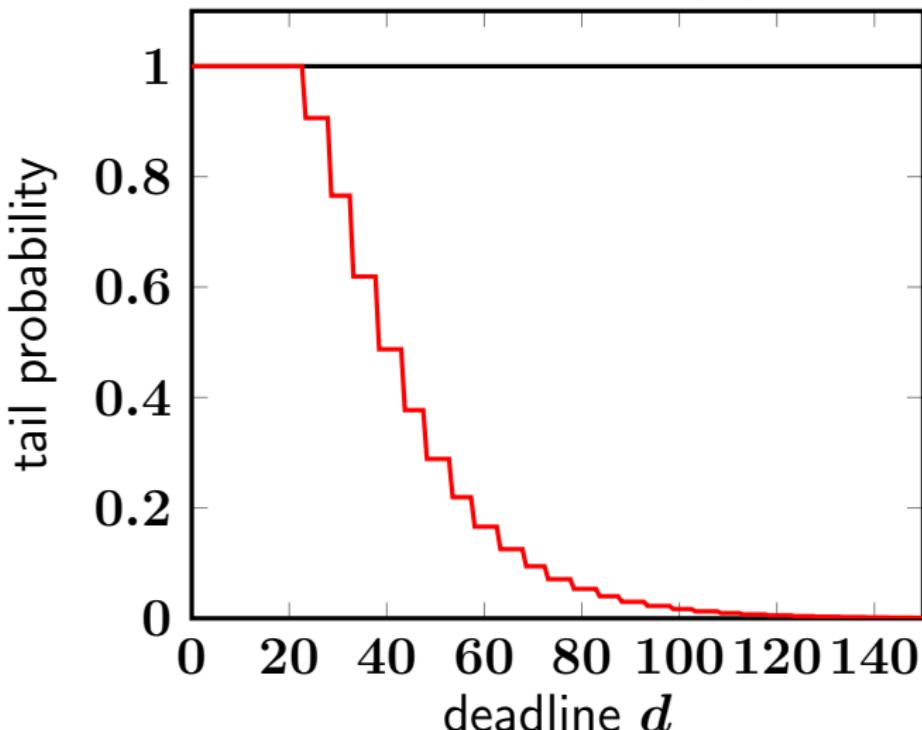
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$$\Pr(T \geq d) \leq \min_{k=0,\dots,K} \frac{u_k}{d^k}$$



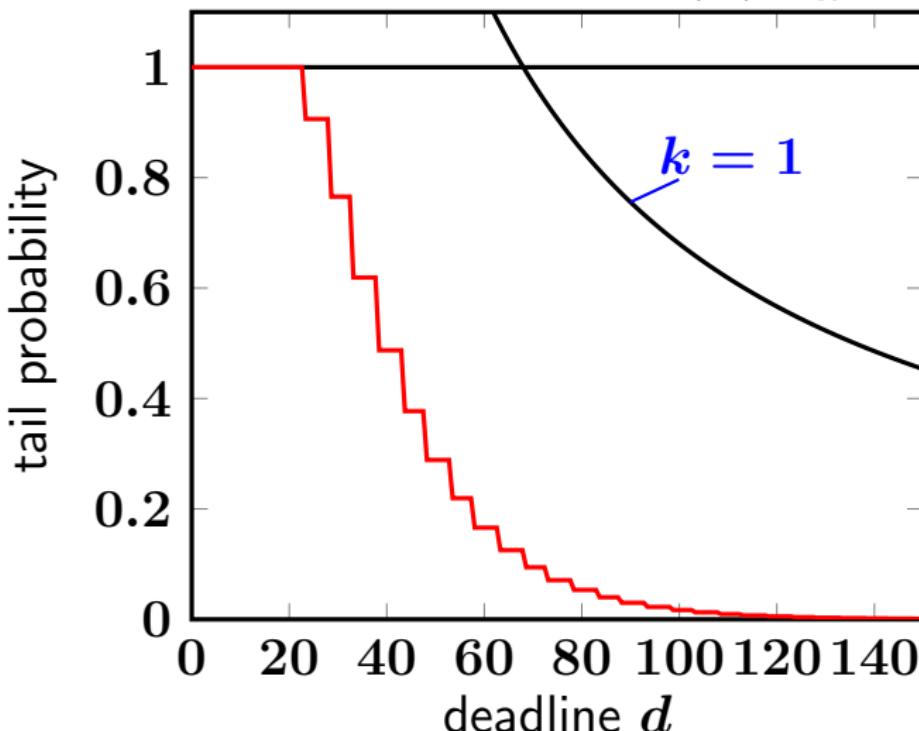
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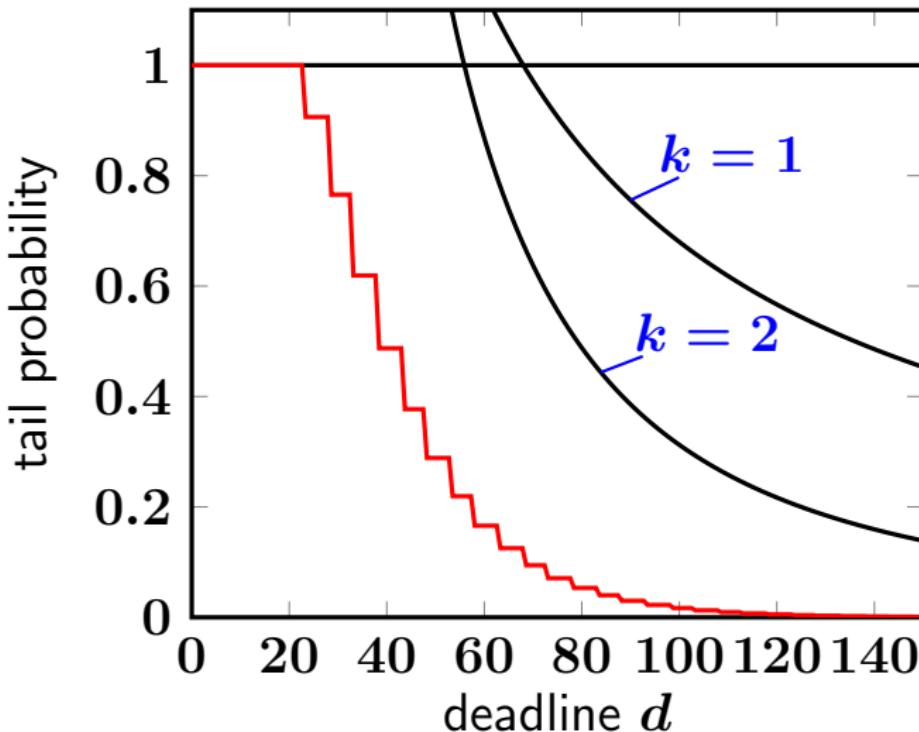
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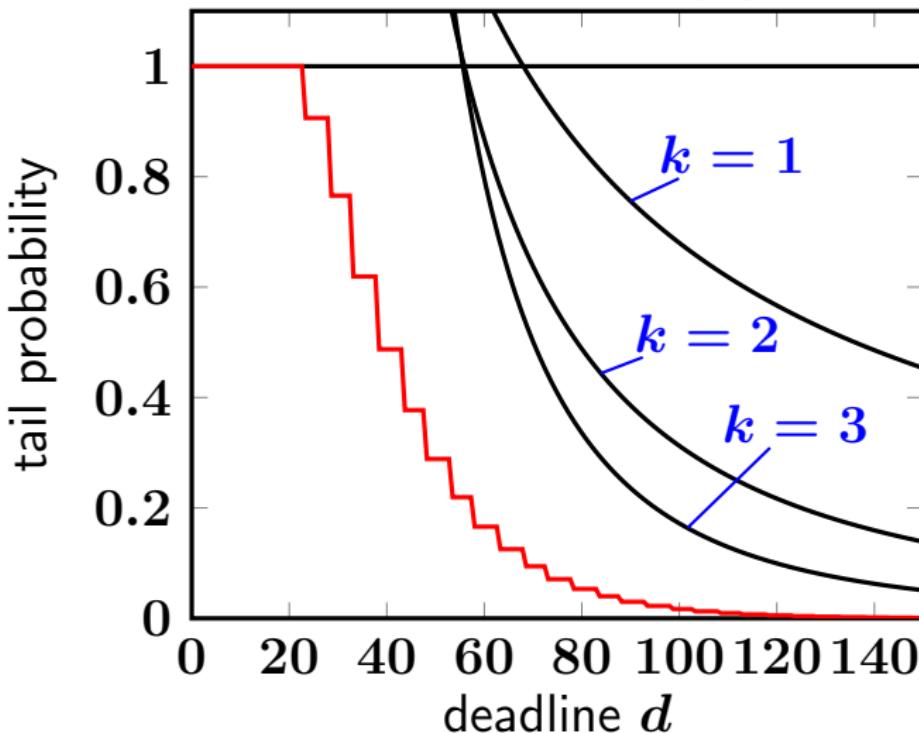
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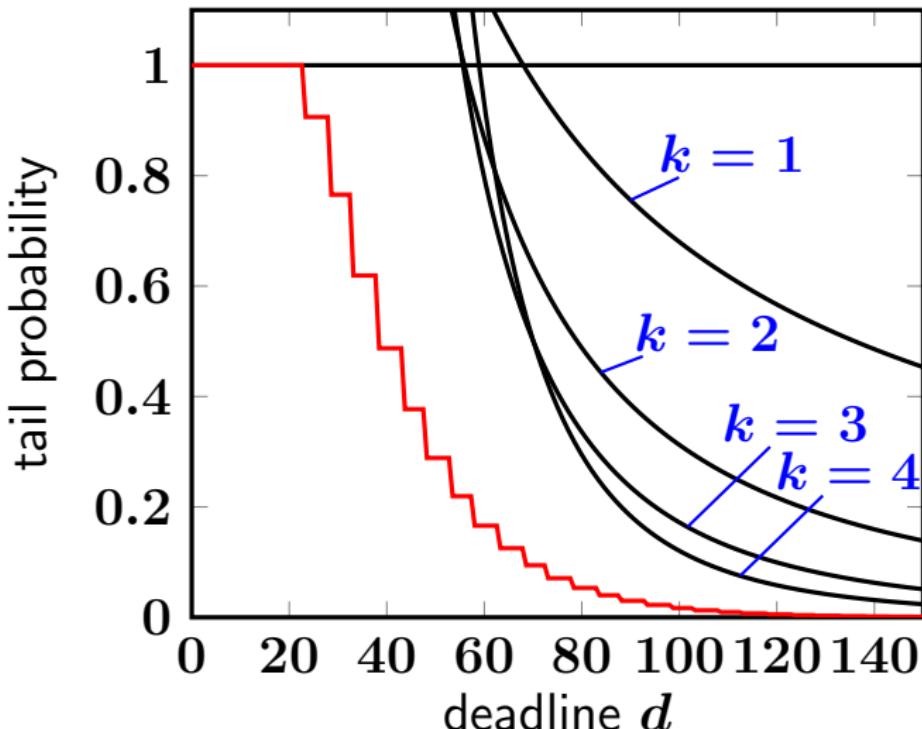
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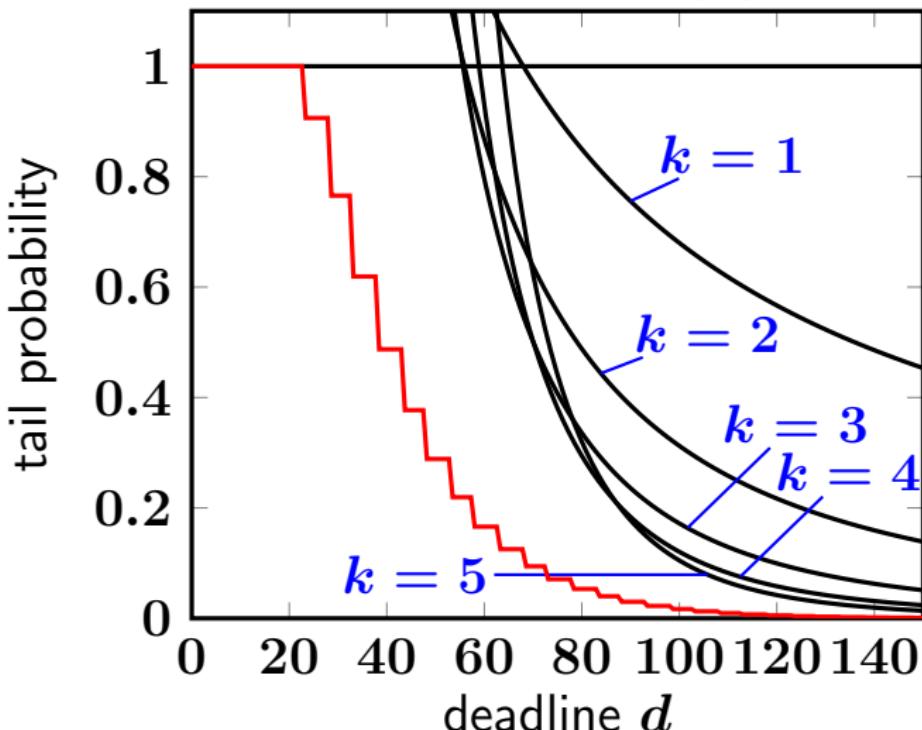
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## Experimental result (2)

A random walk with nondeterminism

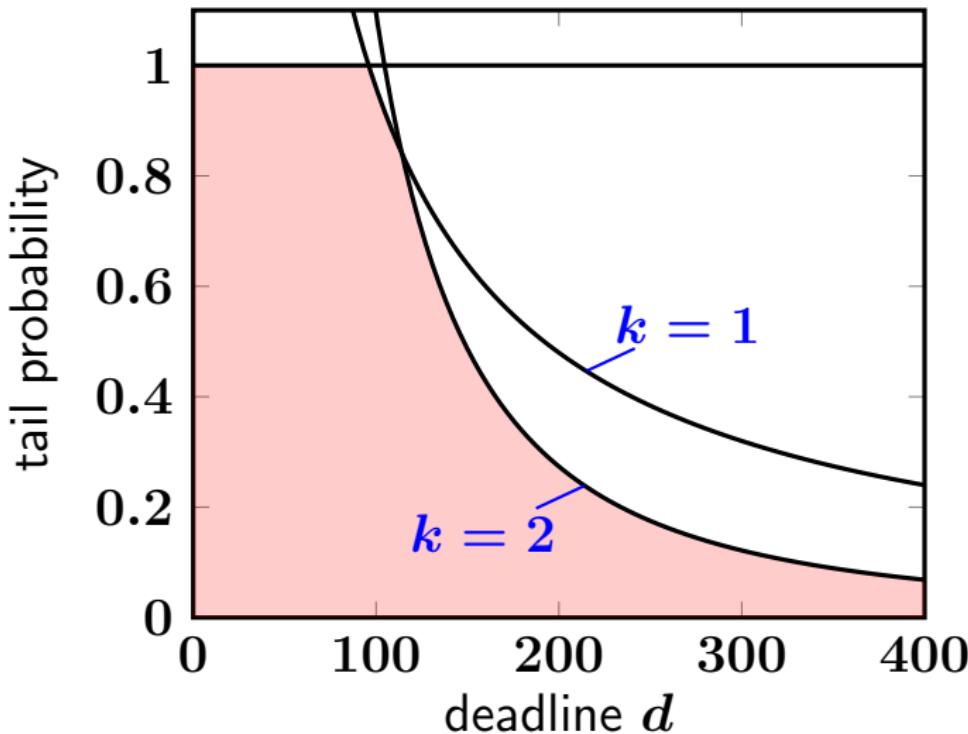
- Linear template

upper bound	execution time
$E[T] \leq 96$	0.020 s
$E[T^2]$ : infeasible	0.029 s

- Polynomial template

upper bound	execution time
$E[T] \leq 95.95$	157.748 s
$E[T^2] \leq 10944.0$	361.957 s

## Experimental result (2)



# Conclusion & Future work

## Conclusion

- New supermartingale for higher moments of runtime
- Applied to obtain upper bounds of tail probabilities
- Tested our method experimentally

## Future work

- Improved treatment of nondeterminism
- Compositional reasoning (cf. [Kaminski et al., ESOP'16])
- Improve implementation (numerical error of SDP solver)