

# SMT-based Counterexample Generation for Markov Chains

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- Complex (embedded) systems everywhere:



- Correct behaviour has to be ensured.
- Verification is needed.
  - ⇒ Counterexamples
  - ⇒ Bounded Model Checking (BMC)
- Some systems have probabilistic elements.
  - ⇒ Stochastic Bounded Model Checking

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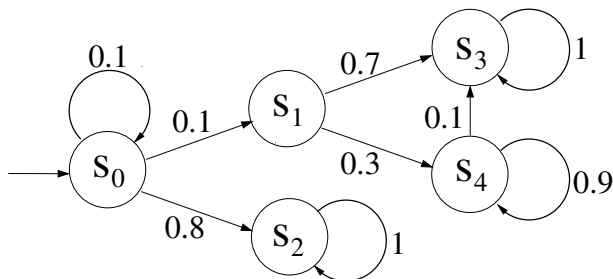
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- **A Discrete-Time Markov Chain (DTMC)**

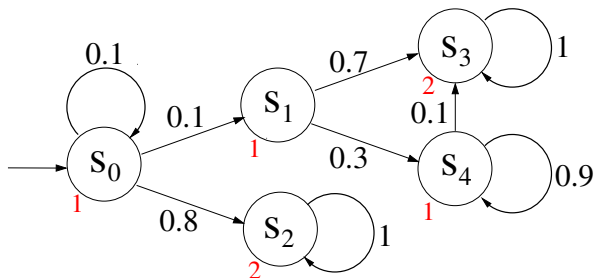
$M = (S, s_I, P, L)$  consists of

- $S$ : finite set of states with initial state  $s_I$ ,
- $P : S \times S \rightarrow [0, 1]$ : matrix of transition probabilities,
- $L : S \rightarrow 2^{AP}$ : labeling function.

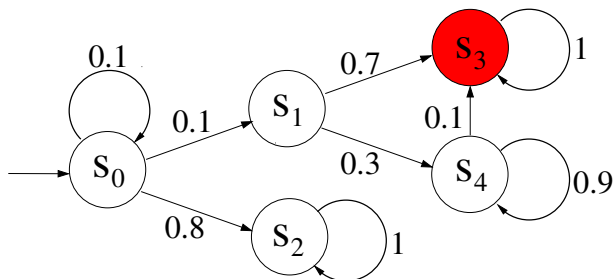


- **A Markov Reward Model (MRM)**

$(M, R)$  consists of a DTMC  $M = (S, s_i, P, L)$  and a reward function  $\mathbf{R} : S \rightarrow \mathbb{R}$ .



# Counterexample for DTMCs (1)

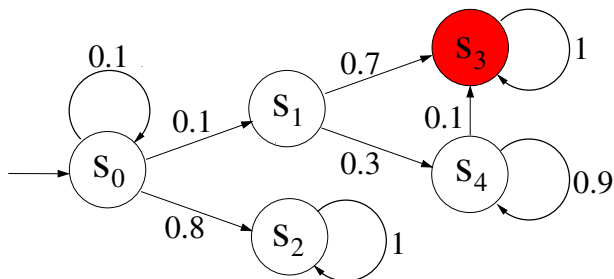


Critical state  $s_3$ .

Should be reached with a probability of at most 0.08:

$$\mathcal{P}_{\leq 0.08}(\top \mathbf{U} s_3)$$

# Counterexample for DTMCs (1)



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Does this property hold?



**Given:** A DTMC  $M$  and a PCTL-property  $\varphi = \mathcal{P}_{\leq p}(aUb)$ .

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- An **evidence** is a finite path  $\pi = s_0, s_1, \dots, s_n$  with  $s_0 = s_I$  and  $\pi \models aUb$ .  $\pi$  is not a prefix of another evidence.

$\pi$  has the probability  $\Pr(\pi) = \prod_{i=0}^{n-1} P(s_i, s_{i+1})$ .

## Counterexample for DTMCs (2)

**Given:** A DTMC  $M$  and a PCTL-property  $\varphi = \mathcal{P}_{\leq p}(aUb)$ .

- An **evidence** is a finite path  $\pi = s_0, s_1, \dots, s_n$  with  $s_0 = s_I$  and  $\pi \models aUb$ .  $\pi$  is not a prefix of another evidence.  
 $\pi$  has the probability  $\Pr(\pi) = \prod_{i=0}^{n-1} P(s_i, s_{i+1})$ .
- A **counterexample** is a set  $C$  of evidences such that  $\Pr(C) > p$ .

# Counterexample for MRMs (1)

**Given:** An **MRM**  $M$  and a PCTL-property  $\varphi = \mathcal{P}_{\leq \rho}(aU^{\mathcal{J}}b)$ ,  $\mathcal{J} \subseteq \mathbb{R}$ .

# Counterexample for MRMs (1)

**Given:** An **MRM**  $M$  and a PCTL-property  $\varphi = \mathcal{P}_{\leq p}(aU^J b)$ ,  $J \subseteq \mathbb{R}$ .

- An **evidence** is a finite path  $\pi = s_0, s_1, \dots, s_n$  with  $s_0 = s_l$  and  $\pi \models aUb$ .  $\pi$  is not a prefix of another evidence.

$\pi$  has the probability  $\Pr(\pi) = \prod_{i=0}^{n-1} P(s_i, s_{i+1})$ .

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# Counterexample for MRMs (1)

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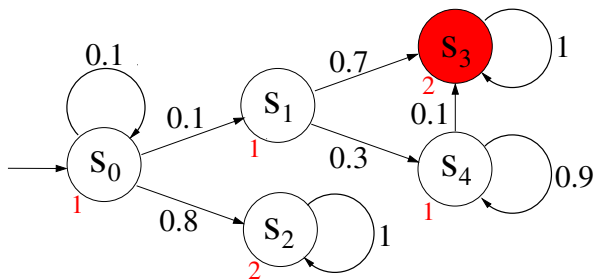
- An **evidence** is a finite path  $\pi = s_0, s_1, \dots, s_n$  with  $s_0 = s_l$  and  $\pi \models aUb$ .  $\pi$  is not a prefix of another evidence.

$\pi$  has the probability  $\Pr(\pi) = \prod_{i=0}^{n-1} P(s_i, s_{i+1})$ .

$\pi$  has the reward  $\text{Re}(\pi) = \sum_{i=0}^{n-1} \mathbf{R}(s_i)$  and  $\text{Re}(\pi) \in \mathcal{J}$ .

- A **counterexample** is a set  $C$  of evidences such that  $\Pr(C) > p$ .

## Counterexample for MRMs (2)



Critical state  $s_3$ .

Should be reached with a probability of at most 0.08, rewards  $\leq 2$ :

$$\mathcal{P}_{\leq 0.08}(\top \mathbf{U}^{[0,2]} s_3)$$

Does this property hold?

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**Explicit:**

**Symbolic:**

## Explicit:

- Shortest path:
  - Aljazzar & Leue, 2010
  - Han, Katoen & Damman, 2009
- Regular expressions:
  - Han, Katoen, & Damman, 2009
- Strongly Connected Components (SCCs):
  - Andrés, D'Argenio & van Rossum, 2008
  - Abraham, Jansen, Wimmer, Katoen & Becker, 2010

## Symbolic:

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## Symbolic:

- Shortest path:
  - Günther, Schuster & Siegle, 2010
- Stochastic BMC (SBMC):
  - Wimmer, Braitling & Becker, 2009

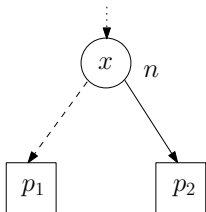
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Consider transition probabilities during search:

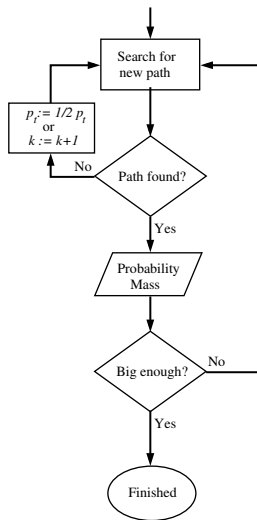
$$I(\mathbf{s}_0) \wedge \bigwedge_{i=0}^{k-1} T_{\text{SMT}}(\mathbf{s}_i, \mathbf{s}_{i+1}, \hat{p}_i) \wedge L_b(\mathbf{s}_k) \wedge \left( \sum_{i=0}^{k-1} \hat{p}_i \geq \log p_t \right)$$

- Solved by an SMT-solver.
- Solution corresponds to an evidence  $\pi$  of length  $k$ ,  $\Pr(\pi) \geq p_t$ .
- Binary search by re-adjusting  $p_t$ .



$$n \leftrightarrow ((x \wedge \hat{p} = \log p_2) \vee (\neg x \wedge \hat{p} = \log p_1))$$

# SMT-based Stochastic BMC (SSBMC) (3)



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SMT allows us to consider rewards:

$$I(\mathbf{s}_0) \wedge \bigwedge_{i=0}^{k-1} T_{\text{SMT}}(\mathbf{s}_i, \mathbf{s}_{i+1}, \hat{p}_i) \wedge L_b(\mathbf{s}_k) \wedge \left( \sum_{i=0}^{k-1} \hat{p}_i \geq \log p_t \right) \\ \wedge \bigwedge_{i=0}^{k-1} R(\mathbf{s}_i, \hat{r}_i) \wedge \left( \min(\mathcal{J}) \leq \sum_{i=0}^{k-1} \hat{r}_i \leq \max(\mathcal{J}) \right)$$

Only paths with rewards within interval  $\mathcal{J}$  are regarded.

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Comparison between SSBMC and SBMC.

## **Benchmarks:**

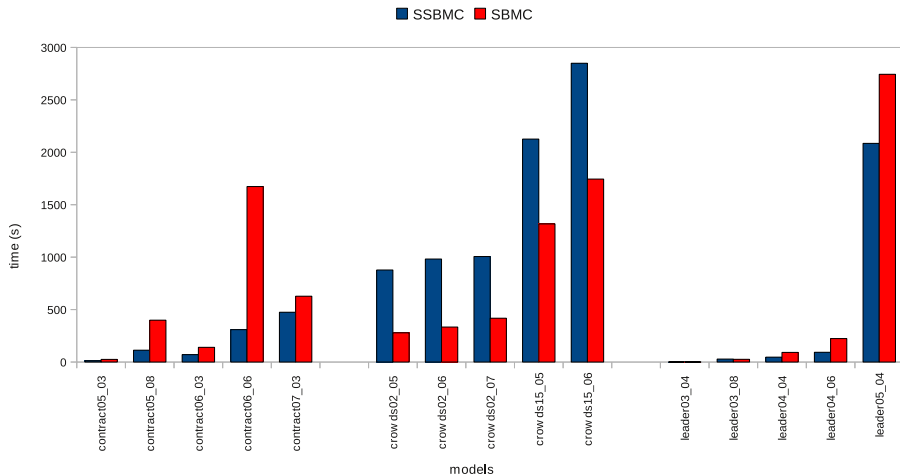
- Contract signing protocol
- Crowds protocol
- Leader election protocol
- Self-stabilizing minimal spanning tree algorithm

## **Setup:**

- Underlying solvers: Yices (SMT-solver), Minisat (SAT-solver).
- Dual Core AMD Opteron with 2.4 GHz per core, 4 GB RAM.
- Time limit: 2 h, memory limit: 2 GB

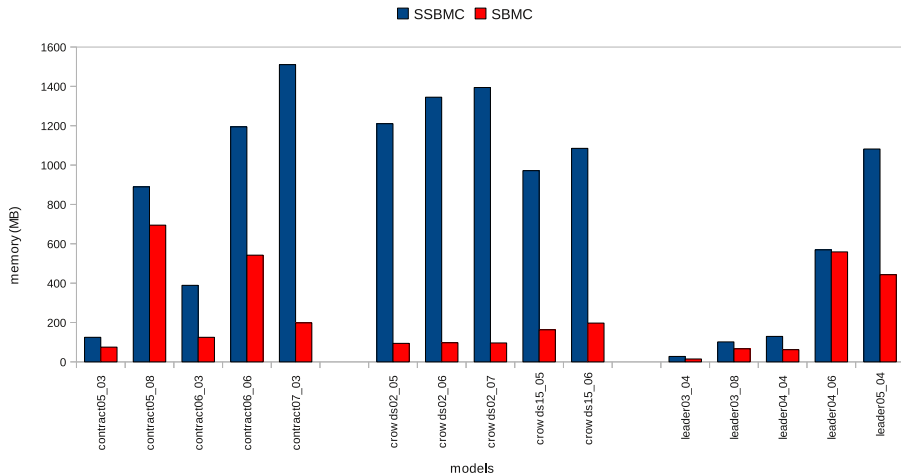
# SMT vs. SAT (1)

Computation Time for Contract, Crowds & Leader



# SMT vs. SAT (2)

Memory Consumption for Contract, Crowds & Leader



- Minimal Spanning Tree:

Name	$p$	$k_{\max}$	SSBMC			SBMC		
			#paths	time	mem.	#paths	time	mem.
mst15	0.049	15	4531	98.58	148.82	> 600000	- TO -	
mst16	0.047	16	4648	107.27	158.25	> 600000	- MO -	
mst18	0.036	18	4073	109.26	164.24	> 600000	- MO -	
mst20	0.034	20	452	19.57	58.21	> 500000	- TO -	

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- SSBMC for MRMs:

Model	$k_{\max}$	$p$	#paths	time	mem.
leader03_02	25	0.06226	360	1.00	29.61
leader04_02	25	0.21875	37376	912.11	1110.54
leader05_02	23	0.14771	4840	40.16	163.06
leader06_02	25	0.12378	32448	907.33	1360.11

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- Conclusion:
  - SMT for Stochastic BMC.
  - Find paths with higher probabilities sooner.
  - Counterexamples for MRMs.
  - Promising results.

- Conclusion:
  - SMT for Stochastic BMC.
  - Find paths with higher probabilities sooner.
  - Counterexamples for MRMs.
  - Promising results.
- Outlook:
  - Optimize the search for paths with higher probabilities.
  - Additional features: Loop detection, bisimulation minimization, transition rewards, . . .
  - More benchmarks, especially MRMs.