

Metric Concurrency Theory

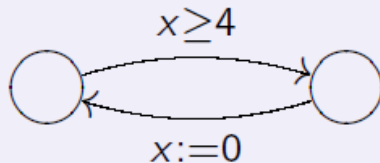
Giovanni Bacci, Giorgio Bacci
Kim G. Larsen, Radu Mardare

Aalborg University
DENMARK



Quantities & Metrics

Quantitative *Models*



Quantitative *Logics*

$$\Pr_{\leq .1}(\Diamond error)$$

Quantitative *Verification*

$$\llbracket \varphi \rrbracket(s) = 0.89$$

$$d(s, t) = 0.09$$

Boolean world

Trace equivalence \equiv

Bisimilarity \sim

$s \sim t$ implies $s \equiv t$

$s \models \varphi$ or $s \not\models \varphi$

$s \sim t$ iff $\forall \varphi : s \models \varphi \Leftrightarrow t \models \varphi$

“Quantification”

Linear distance d_L

Branching distance d_B

$$d_L(s, t) \leq d_B(s, t)$$

$\llbracket \varphi \rrbracket(s)$ is a quantity

$$d_B(s, t) = \sup_{\varphi} d(\llbracket \varphi \rrbracket(s), \llbracket \varphi \rrbracket(t))$$

Markov Chains & Probabilistic Bisimulation

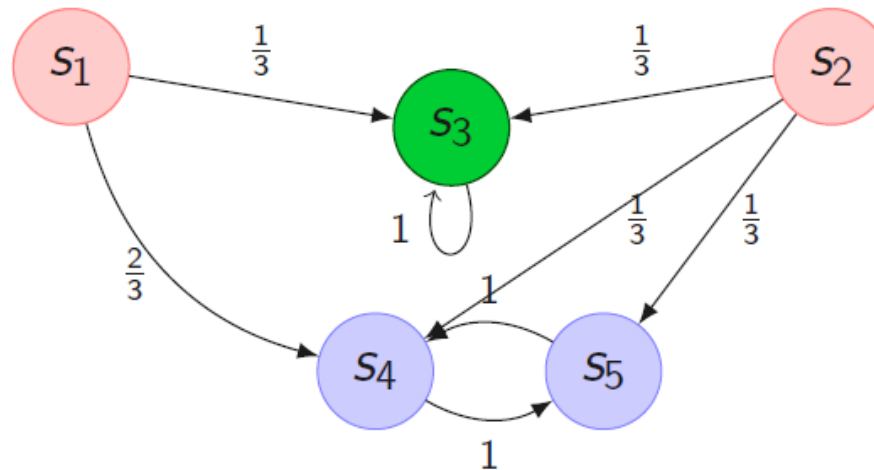
$$\mathcal{M} = (S, \Sigma, \pi, \ell)$$

S : finite set of states

Σ : set of labels

$\pi : S \times S \rightarrow [0, 1]$

$\ell : S \rightarrow \Sigma$.



Markov Chains & Probabilistic Bisimulation

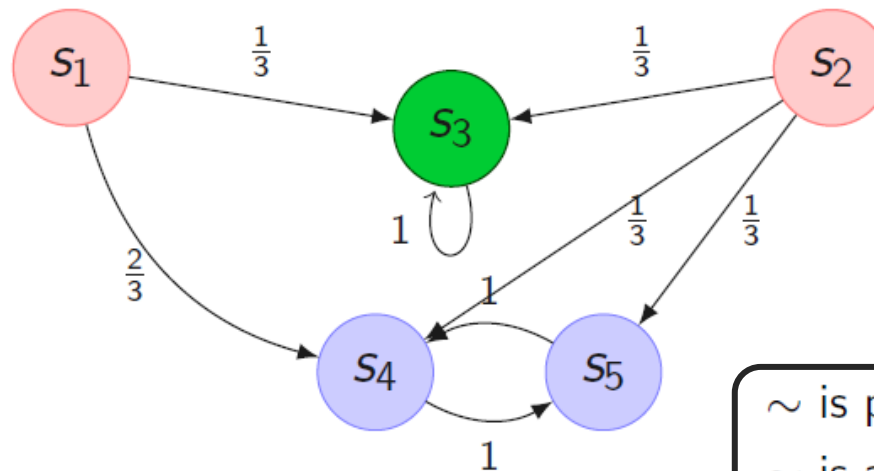
Probabilistic Bisimulation

[LS]

Equivalence relation $R \subseteq S \times S$ such that

$$s R t \implies \begin{cases} \ell(s) = \ell(t) \\ \forall R\text{-equiv. class } C. \sum_{u \in C} \pi(s, u) = \sum_{v \in C} \pi(t, v) \end{cases}$$

$s \sim t$ iff $s R t$ for some probabilistic bisimulation R .



\sim is polynomial-time decidable.
 \sim is a congruence.

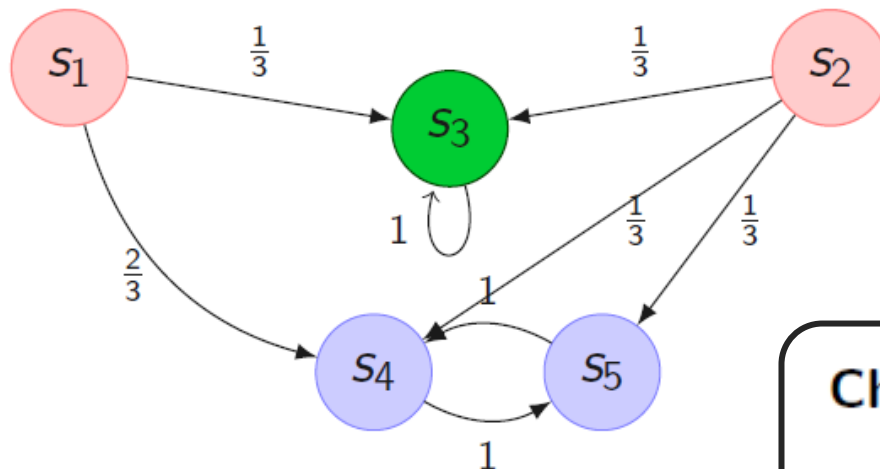
Markov Chains & Probabilistic Bisimulation

Probabilistic Modal Logic

$$F ::= p \mid \neg F \mid F_1 \wedge F_2 \mid \Diamond_{\geq \mu} F$$

where $p \in AP$ and $\mu \in [0, 1]$.

$$s \models \Diamond_{\geq \mu} F \text{ iff } \sum_{t \models F} \pi(s, t) \geq \mu$$



$$s_1, s_2 \models \Diamond_{\geq 0.5} \bullet$$

Characterization

$$s \sim t \text{ iff } (\forall F. s \models F \iff t \models F)$$

Markov Chains & Probabilistic Bisimulation

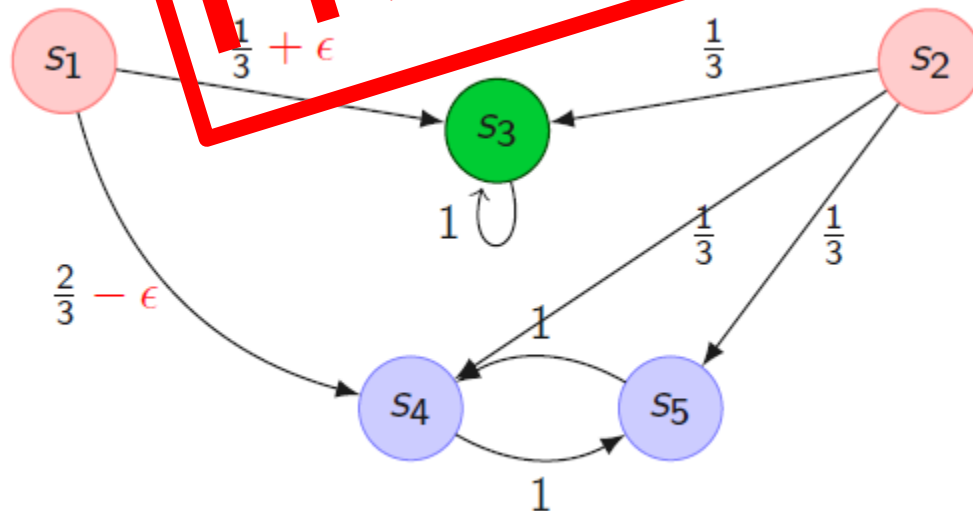
Probabilistic Bisimulation

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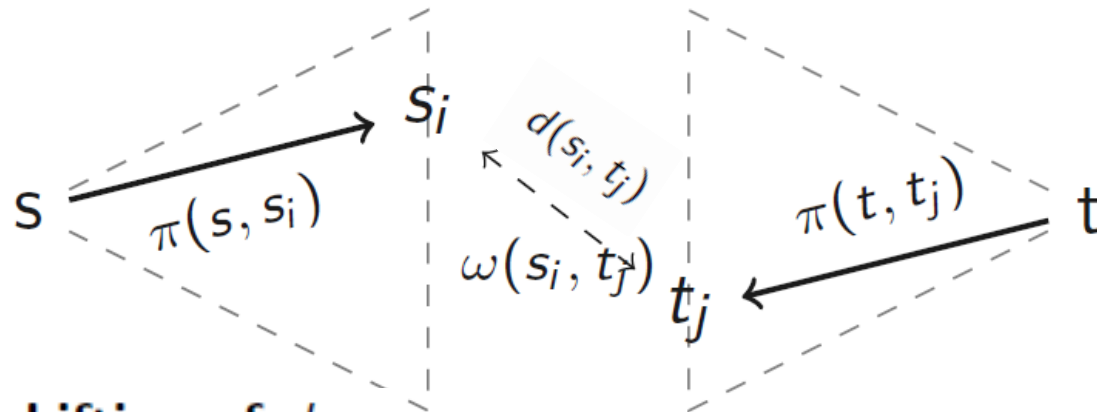
From Equivalences to Distances

Pseudometrics $d: S \times S \rightarrow \mathbb{R}_{\geq 0}$ are the quantitative analogue of an equivalence relation

equivalence		pseudometric
$s \equiv s$	\rightsquigarrow	$d(s, s) = 0$
$s \equiv t \implies t \equiv s$	\rightsquigarrow	$d(s, t) = d(t, s)$
$s \cong u \wedge u \cong t \implies s \cong t$	\rightsquigarrow	$d(s, u) + d(u, t) \geq d(s, t)$

Bisimilarity Pseudometric: $d(s, t) = 0 \iff s \sim t$

Fixed Point Characterization



Kantorovich Lifting of d :

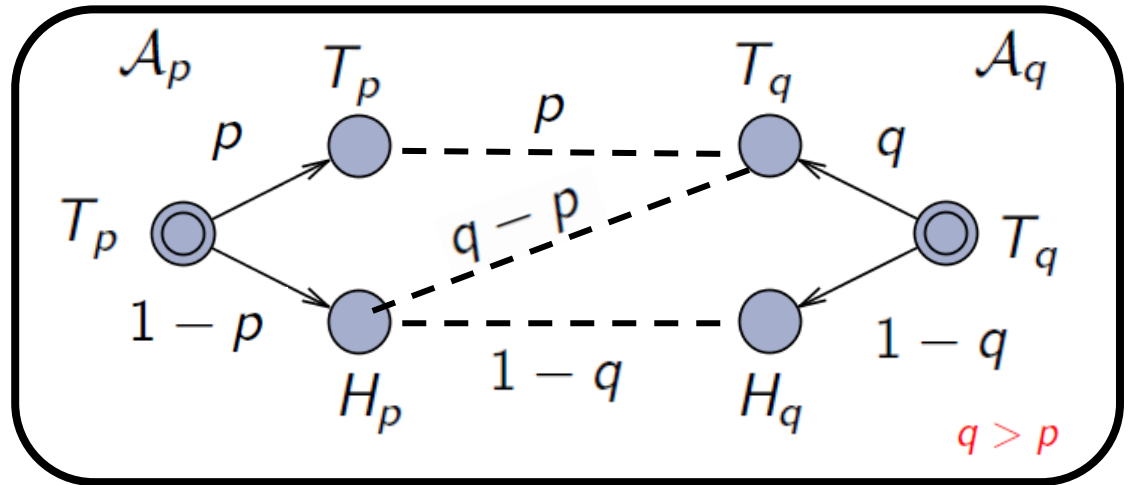
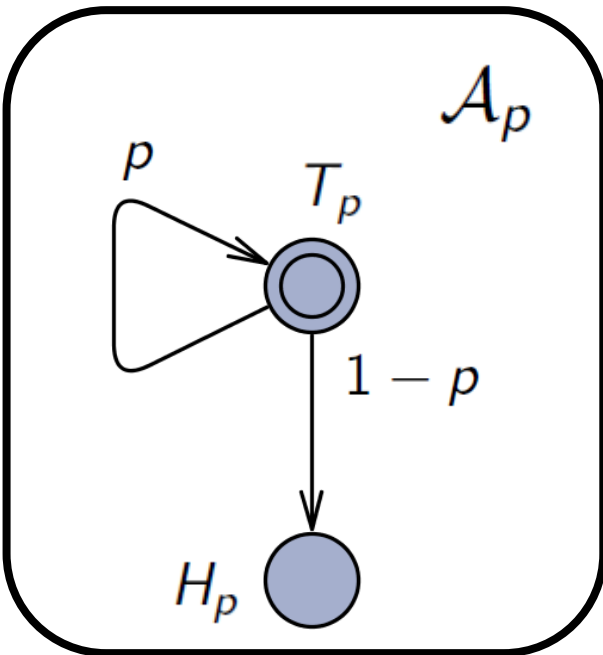
$$K(d)(s, t) = \min \left\{ \sum_{u,v \in S} d(u, v) \cdot \omega(u, v) \mid \begin{array}{l} \forall u \in S \sum_{v \in S} \omega(u, v) = \pi(s, u) \\ \forall v \in S \sum_{u \in S} \omega(u, v) = \pi(t, v) \end{array} \right\}$$

matching
 $\omega \in \pi(s, \cdot) \otimes \pi(t, \cdot)$

$d_{\mathcal{K}}(s, s')$ is the **least fixed point** to the following operator on pseudometrics:

$$\mathcal{K}(d)(s, s') = \max \{ |ls - ls'|, K(d)(s, s') \}$$

Coin Example



$$d_{\mathcal{K}}(T_p, T_q) = p \cdot d_{\mathcal{K}}(T_p, T_q) + (q - p) \cdot 1$$

Thus $d_{\mathcal{K}}(T_p, T_q) = \frac{q-p}{1-p} \rightarrow 0$ when $q \rightarrow p$.

Bisimulation Pseudometric: $d_{\mathcal{K}}(s, s') = 0 \iff s \sim s'$.

Complexity: $d_{\mathcal{K}}$ can be computed in polynomial time.

Upper Bound:

$$\sup_{\phi \in \text{LTL}} |\mathbb{P}_s(\phi) - \mathbb{P}_{s'}(\phi)| \leq d_{\mathcal{K}}(s, s')$$

Tools: Efficient on-the-fly algorithm for computing $d_{\mathcal{K}}$ exactly has been developed.

Compositionality: Process constructs are non-expanding, contracting or continuous with respect to $d_{\mathcal{K}}$.

Characterization: $d_{\mathcal{F}} = d_{\mathcal{K}}$

Josee Desharnais, Vineet Gupta, Radha Jagadeesan, Prakash Panangaden: Metrics for Labeled Markov Systems. CONCUR 1999:

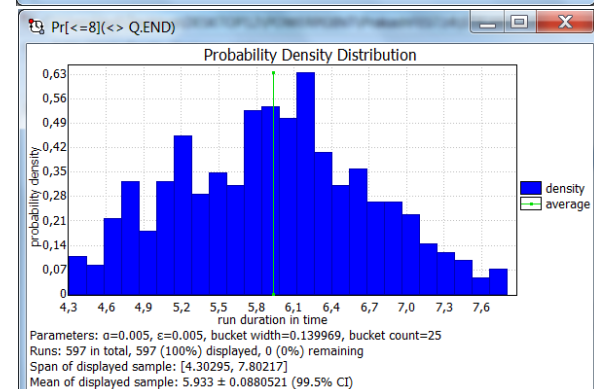
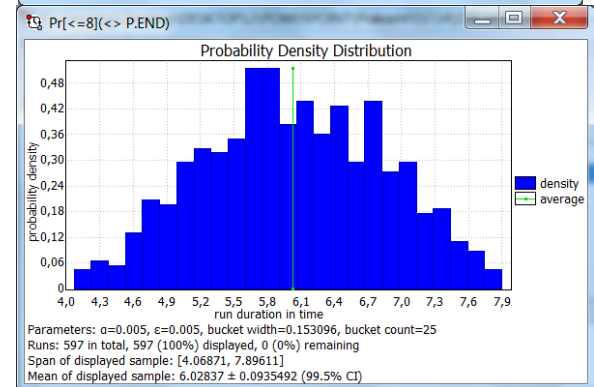
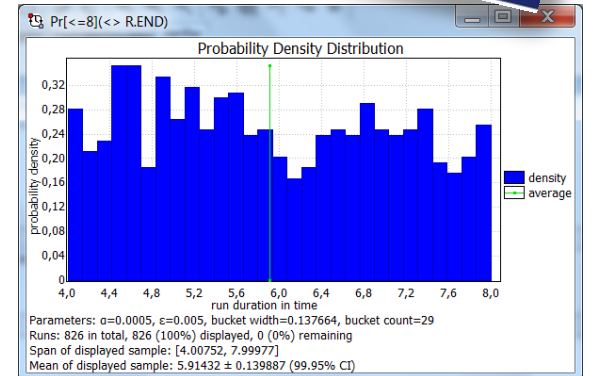
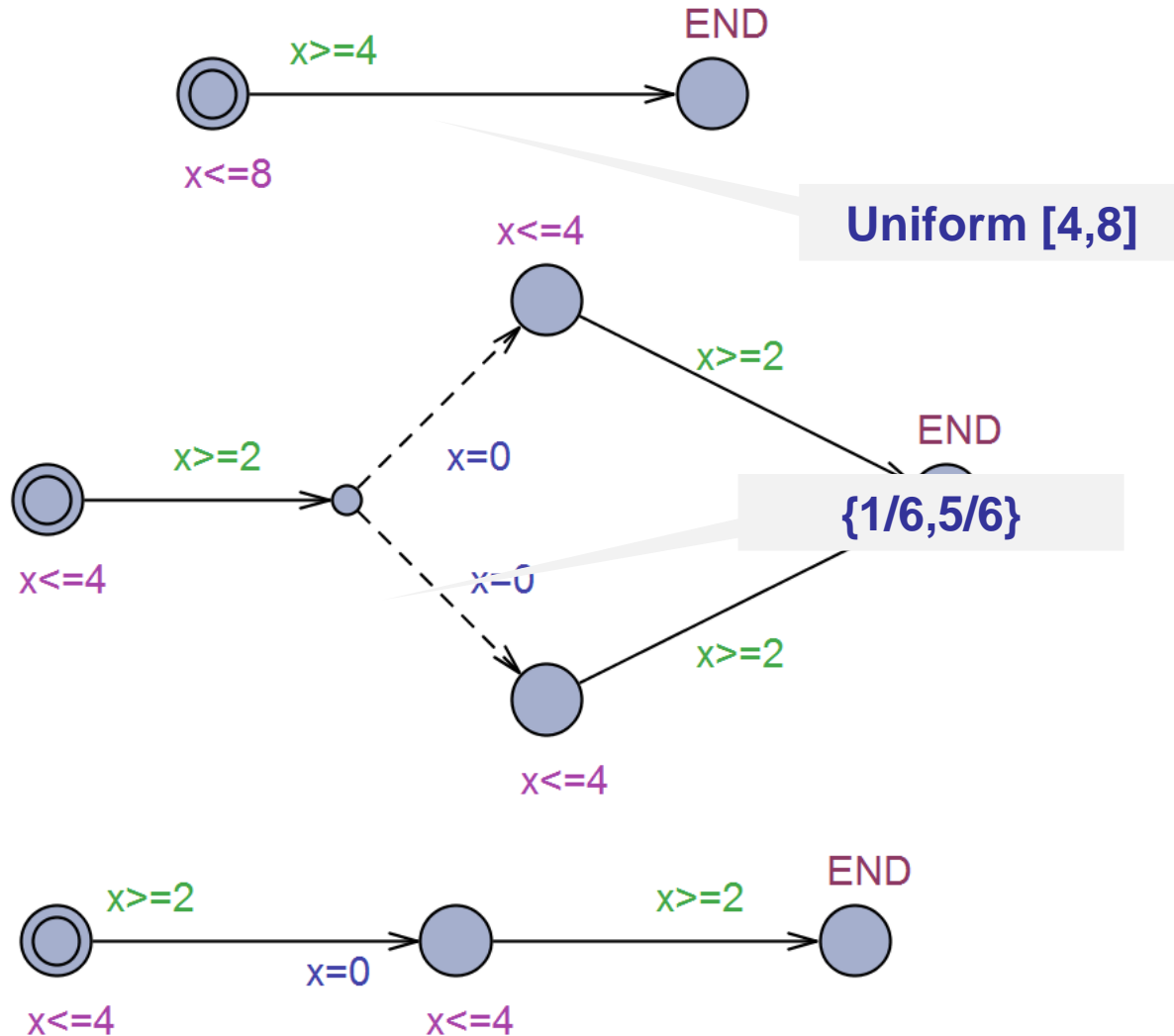
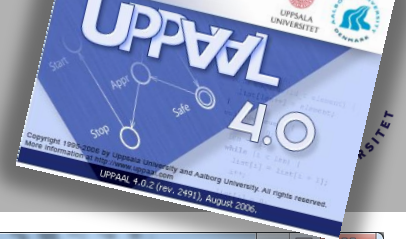
D. Chen, F. van Breugel, and J. Worrell. On the Complexity of Computing Probabilistic Bisimilarity. FOSSACS2012

G. Bacci, G. Bacci, K. G. Larsen, and R. Mardare. On-the-Fly Exact Computation of Bisimilarity Distances. TACAS2013

G. Bacci, G. Bacci, K. G. Larsen, and R. Mardare. Topologies of stochastic markov models: Computational aspects.

R. D'Argenio, Gebler, David Lee: Axiomatizing Bisimulation Equivalences and Metrics from Probabilistic SOS Rules. FoSSaCS 2014

Stochastic Timed Automata

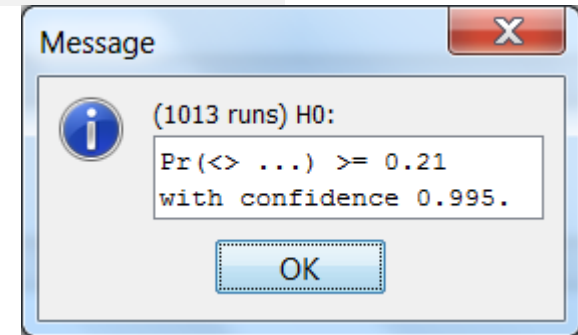


Statistical Model Checking

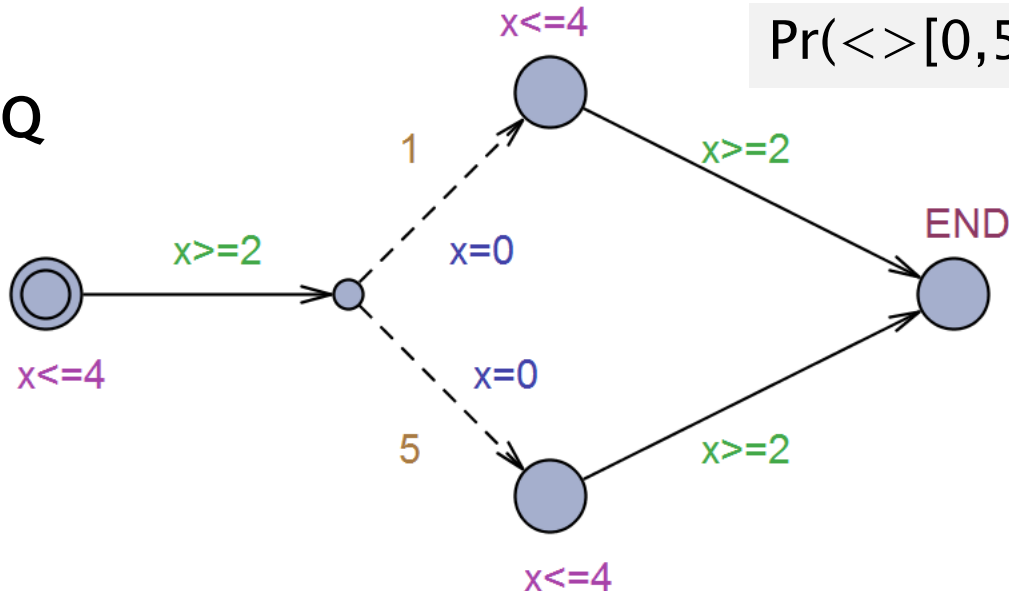
R



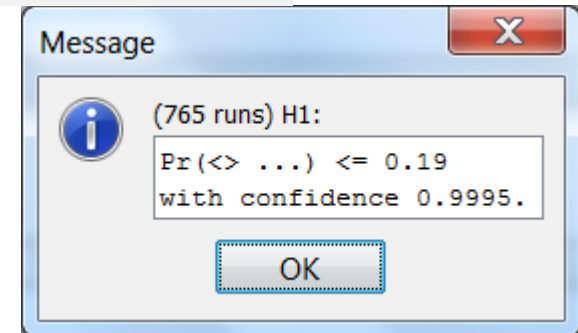
$$\Pr(\langle \rangle [0,5] \text{ R.END}) \geq 0.2$$



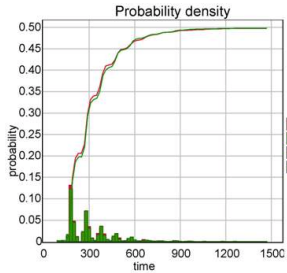
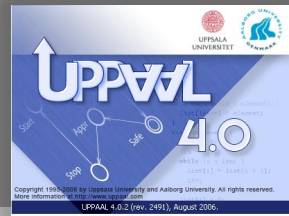
Q



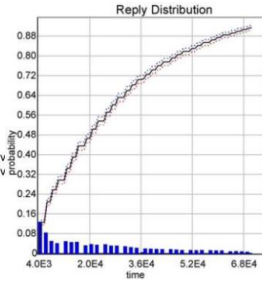
$$\Pr(\langle \rangle [0,5] \text{ Q.END}) \geq 0.2$$



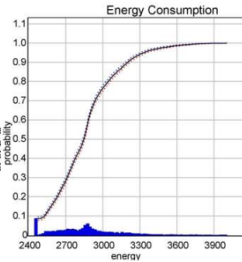
Statistical Model Checking



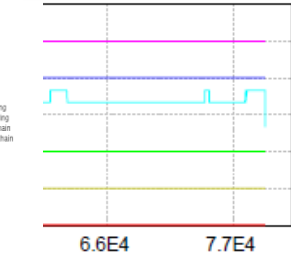
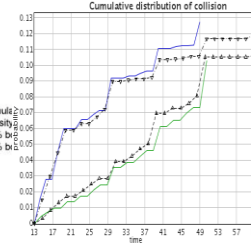
FIREWIRE



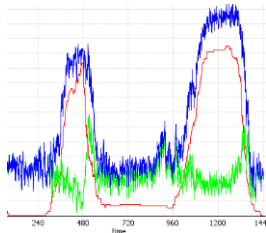
BLUETOOTH



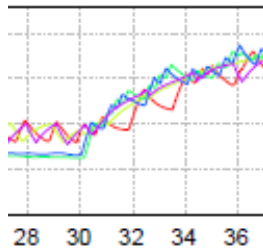
10 node LMAC



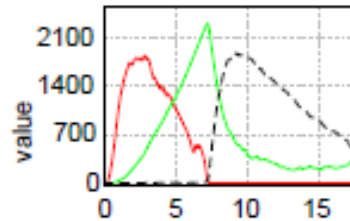
Schedulability Analysis for Mix Cr Sys



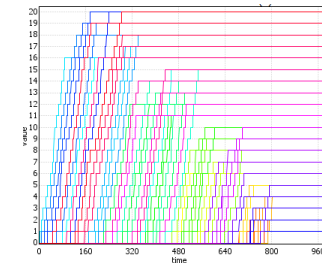
Smart Grid Demand / Response



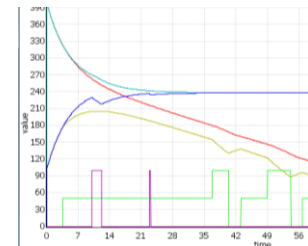
Energy Aware Buildings



Genetic Oscillator (HBS)



Passenger Seating in Aircraft

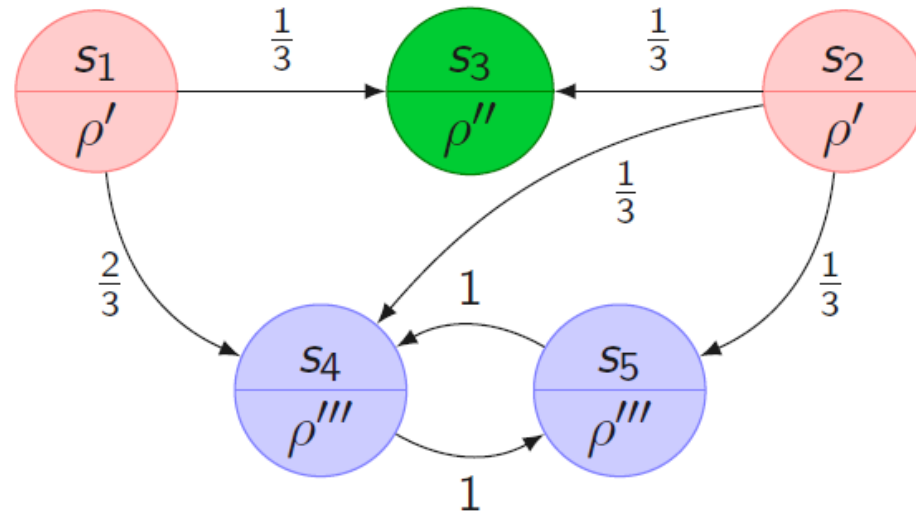


Battery Scheduling

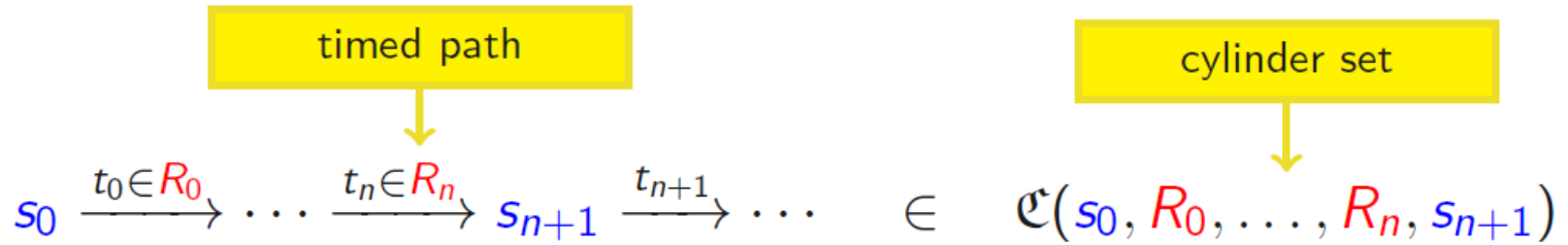
Semi-Markov Processes

- + S finite set of states
- + $\tau: S \rightarrow \mathcal{D}(S)$ transition probability function
- + $\rho: S \rightarrow \mathcal{D}(\mathbb{R}_+)$ residence-time distribution function
- + $\ell: S \rightarrow 2^{AP}$ labeling function (AP atomic propositions)

$$\mathcal{M} = (S, \tau, \rho, \ell)$$



Probability Measure on Runs



$$\mathbb{P}_s^{\mathcal{M}}(\mathfrak{C}(s_0)) = \begin{cases} 1 & \text{if } s_0 = s \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{P}_s^{\mathcal{M}}(\mathfrak{C}(s_0, R_0, \dots, R_n, s_{n+1})) = \mathbb{P}_s^{\mathcal{M}}(\mathfrak{C}(s_0, R_0, \dots, R_{n-1}, s_n)) \cdot \rho(s_n)(R_n) \cdot \tau(s_n)(s_{n+1})$$

delay probability

transition probability

MTL

$$\varphi ::= p \mid \perp \mid \varphi \rightarrow \varphi \mid X^{[t,t']} \varphi \mid \varphi U^{[t,t']} \varphi,$$

timed path

$\mathcal{M}, \pi \models \varphi$

timed
next

timed
until

$\mathcal{M}, \pi \models p$

if $p \in \ell(\pi[0])$,

$\mathcal{M}, \pi \models \perp$

never,

$\mathcal{M}, \pi \models \varphi \rightarrow \psi$

if $\mathcal{M}, \pi \models \psi$ whenever $\mathcal{M}, \pi \models \varphi$,

$\mathcal{M}, \pi \models X^{[t,t']} \varphi$

if $\pi\langle 0 \rangle \in [t, t']$, and $\mathcal{M}, \pi|_1 \models \varphi$,

$\mathcal{M}, \pi \models \varphi U^{[t,t']} \psi$

if $\exists i > 0$ s.t. $\sum_{k=0}^{i-1} \pi\langle k \rangle \in [t, t']$, $\mathcal{M}, \pi|_i \models \psi$,
and $\mathcal{M}, \pi|_j \models \varphi$ whenever $0 \leq j < i$.

accumulated
delay

Variational Pseudo Metrics

Lemma

$\varphi \in MTL \implies \llbracket \varphi \rrbracket_{\mathcal{M}} = \{\pi \mid \mathcal{M}, \pi \models \varphi\}$ is measurable

$$\delta_{MTL}^{\mathcal{M}}(s, s') = \sup_{\varphi \in MTL} |\mathbb{P}_s^{\mathcal{M}}(\llbracket \varphi \rrbracket_{\mathcal{M}}) - \mathbb{P}_{s'}^{\mathcal{M}}(\llbracket \varphi \rrbracket_{\mathcal{M}})|$$

Lemma

$\mathcal{A} \in DTA \implies \llbracket \mathcal{A} \rrbracket_{\mathcal{M}} = \{\pi \mid \pi \in \mathcal{L}(\mathcal{A})\}$ is measurable

$$\delta_{DTA}^{\mathcal{M}}(s, s') = \sup_{\mathcal{A} \in DTA} |\mathbb{P}_s^{\mathcal{M}}(\llbracket \mathcal{A} \rrbracket_{\mathcal{M}}) - \mathbb{P}_{s'}^{\mathcal{M}}(\llbracket \mathcal{A} \rrbracket_{\mathcal{M}})|$$

**NP-hard !!
Decidable ??**

Theorem (MTL and DTA variational distances coincide)

$$\delta_{MTL}^{\mathcal{M}} = \delta_{DTA}^{\mathcal{M}}$$

1-RDTA & Denseness

1-RDTA — single-clock resetting DTAs

Lemma (1-RDTAs are $\mathbb{P}^{\mathcal{M}}$ -dense in DTAs)

For any $\mathcal{A} \in DTA$ and any $\varepsilon > 0$, there exists $\mathcal{B} \in 1\text{-RDTA}$ s.t.

$$|\mathbb{P}_s^{\mathcal{M}}(\llbracket \mathcal{A} \rrbracket_{\mathcal{M}}) - \mathbb{P}_s^{\mathcal{M}}(\llbracket \mathcal{B} \rrbracket_{\mathcal{M}})| < \varepsilon$$

Let $\delta_{1\text{-RDTA}}^{\mathcal{M}}(s, s') = \sup_{\mathcal{B} \in 1\text{-RDTA}} |\mathbb{P}_s^{\mathcal{M}}(\llbracket \mathcal{B} \rrbracket_{\mathcal{M}}) - \mathbb{P}_{s'}^{\mathcal{M}}(\llbracket \mathcal{B} \rrbracket_{\mathcal{M}})|$, then

Theorem

$$\delta_{DTA}^{\mathcal{M}} = \delta_{1\text{-RDTA}}^{\mathcal{M}}$$

Enable approximate MC of
MTL for CTMC

Computable Upper Bound

$$F^{\mathcal{M}}(d)(s, s') = \begin{cases} 1 & \text{if } \ell(s) \neq \ell(s') \\ \alpha + (1 - \alpha) \cdot K(d)(\tau(s), \tau(s')) & \text{otherwise} \end{cases}$$

prob. same delay time

prob. different delay time
 $\|\rho(s) - \rho(s')\|_{TV}$

Kantorovich distance w.r.t. d

Bisimilarity Distance

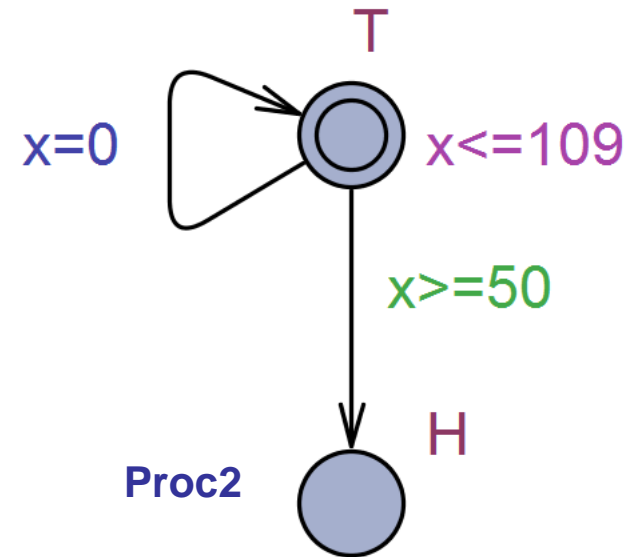
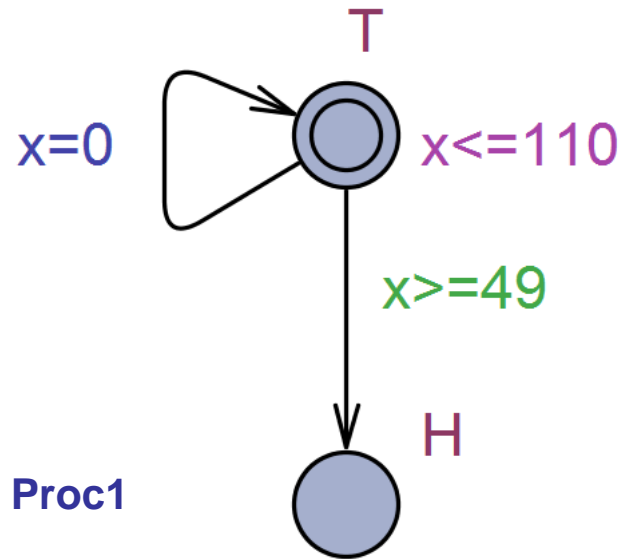
$d_{bisim}^{\mathcal{M}} : S \times S \rightarrow [0, 1]$ is the least fixed point of $F^{\mathcal{M}}$

Theorem (Upper bound)

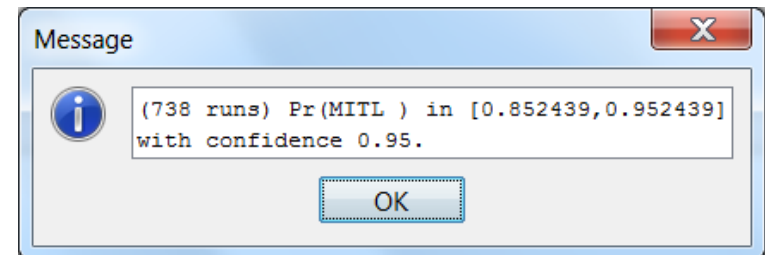
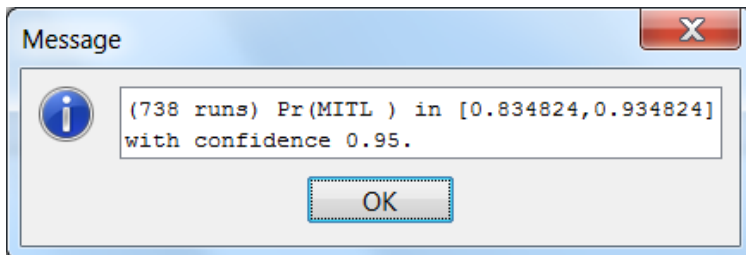
$$\delta^{\mathcal{M}}(s, s') \leq d_{bisim}^{\mathcal{M}}(s, s')$$

Polynomial

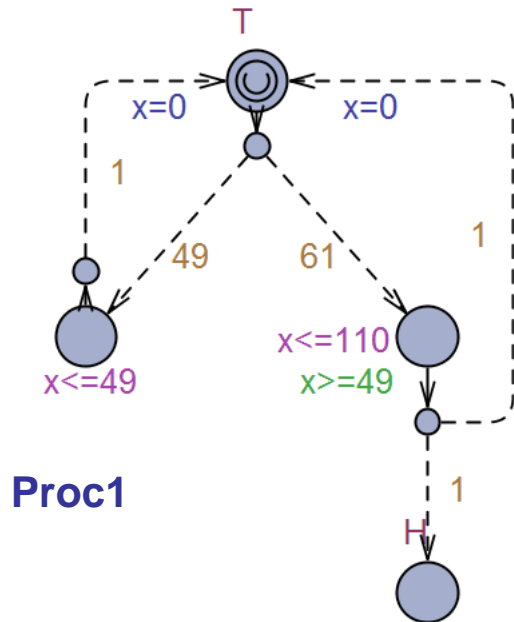
Timed Coins – STA



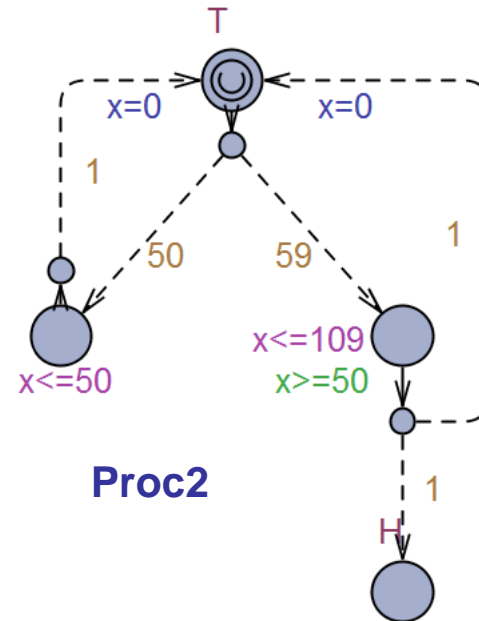
$\text{Pr}(\text{Proci.T } U[5;400] \text{ Proci.H})$



Timed Coins – SMP

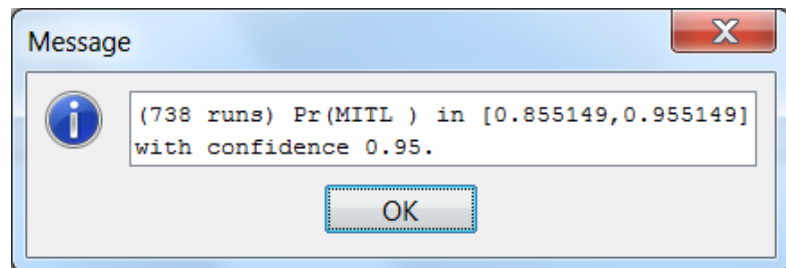
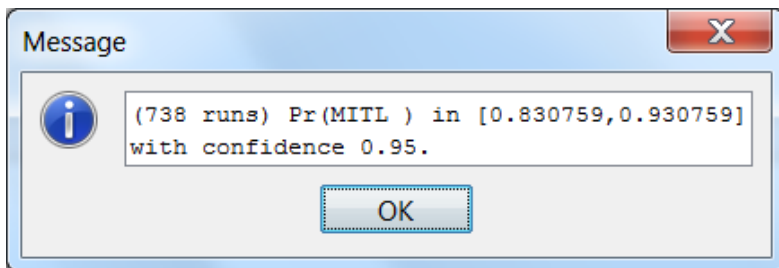


Proc1

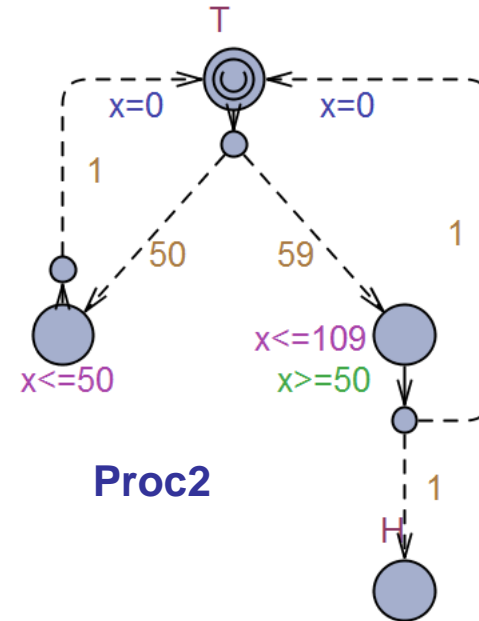
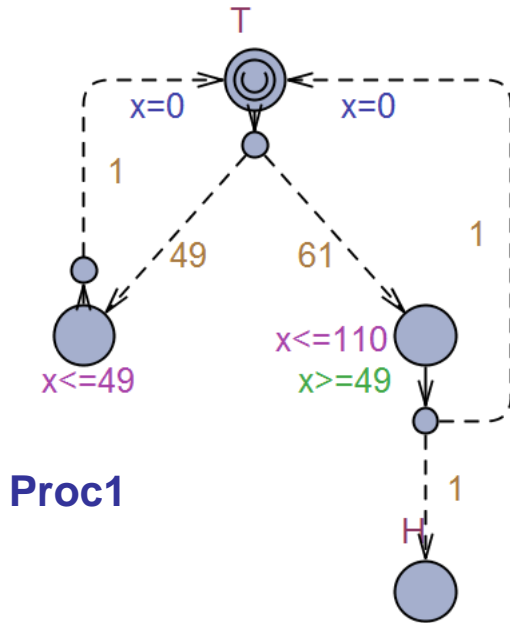


Proc2

$\Pr(\text{Proc1.T } U[5;400] \text{ Proc1.H})$



Timed Coins – SMP



$$\|U(49,110)(E) - U(50,109)(E)\|_E = \frac{2}{61}$$

$$d(T_1, T_2) = 0.132$$

BISIMDIST is a Mathematica[®] library that provides two packages:

MCDIST

MDPDIST

CTMCDIST

- + Data structures (model definition)
- + Data structure manipulators & visualizers
- + Procedure for computing bisimilarity distances (*on-the-fly!*)
 - + approximated methods (from known upper-bounds)
 - + future-discount
- + bisimilarity classes / quotient by bisimilarity

Library + Tutorials

<http://people.cs.aau.dk/giovbacci/tools.html>



- Decidability of **Total Variational MTL distance** ?
- How big is the gap between TV distance and bisimulation distance ?
- **Denseness of CTMC** (1-RDTA) in the class of Semi Markov Process with respect to bisimulation distance ?
- Extension to **Generalised Semi Markov Processes**
- **Weak** bisimulation distances
- **Parameter continuity**, i.e. $d(s(p_1), s(p_2)) \rightarrow 0$ when $p_1 \rightarrow p_2$?