

# A Hemimetric Extension of Simulation for Semi-Markov Decision Processes

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Mathias Ruggaard Pedersen, Giorgio Bacci, Kim Guldstrand  
Larsen, and Radu Mardare

`{mrp, grbacci, kgl, mardare}@cs.aau.dk`

Department of Computer Science, Aalborg University, Denmark



AALBORG UNIVERSITY  
DENMARK

# Agenda



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# Introduction

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## Background



Semi-Markov decision processes have

- ▶ real-time behaviour,
- ▶ probabilistic behaviour, and
- ▶ non-deterministic behaviour.



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# Introduction

## Background

Semi-Markov decision processes have

- ▶ real-time behaviour,
- ▶ probabilistic behaviour, and
- ▶ non-deterministic behaviour.

They have been used to model

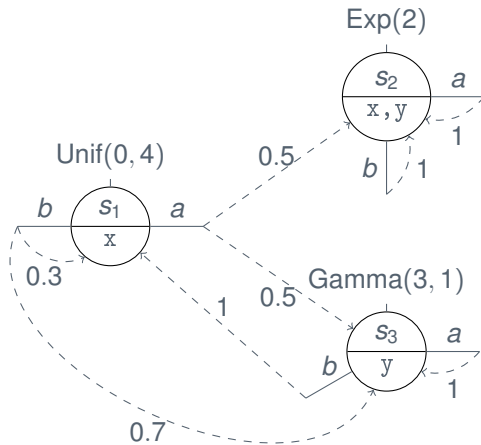
- ▶ power plants,
- ▶ transportation infrastructure,
- ▶ revenue management systems,
- ▶ bridge maintenance,
- ▶ and more.





# Introduction

## Semi-Markov decision processes





# Introduction

## Semi-Markov decision processes

A Semi-Markov decision process is given by

- ▶  $S$  a countable set of states,
- ▶  $\tau : S \times A \rightarrow \mathcal{D}(S)$  the transition function,
- ▶  $\rho : S \rightarrow \mathcal{D}(\mathbb{R}_{\geq 0})$  the residence-time function, and
- ▶  $L : S \rightarrow 2^{AP}$  the labelling function.



# Introduction

## Simulation

### Definition

A relation  $R \subseteq S \times S$  is a *simulation relation* if for all  $(s_1, s_2) \in R$

- ▶  $L(s_1) = L(s_2)$ ,
- ▶  $F_{s_1}(t) \leq F_{s_2}(t)$  for all  $t \in \mathbb{R}_{\geq 0}$ , and
- ▶ for all  $a \in A$  there exists a *coupling*  $\Delta_a: S \times S \rightarrow [0, 1]$  between  $\tau(s_1, a)$  and  $\tau(s_2, a)$  such that
  - ▶  $\Delta_a(s, s') > 0$  implies  $(s, s') \in R$ ,
  - ▶  $\tau(s_1, a)(s) = \sum_{s' \in S} \Delta_a(s, s')$  for all  $s \in S$ , and
  - ▶  $\tau(s_2, a)(s') = \sum_{s \in S} \Delta_a(s, s')$  for all  $s' \in S$ .

$s_1 \preceq s_2$  –  $s_2$  simulates  $s_1$



# Introduction

## Simulation (alternative)

### Definition (alternative)

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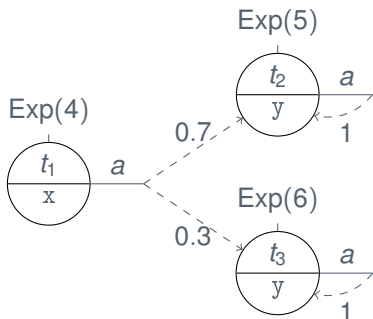
- ▶  $L(s_1) = L(s_2)$ ,
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- ▶ for all  $a \in A$  and  $C \subseteq S$ ,  $\tau(s_1, a)(C) \leq \tau(s_2, a)(R(C))$ .

$R(C)$  upward closure of  $C$ .



# Introduction

## Example

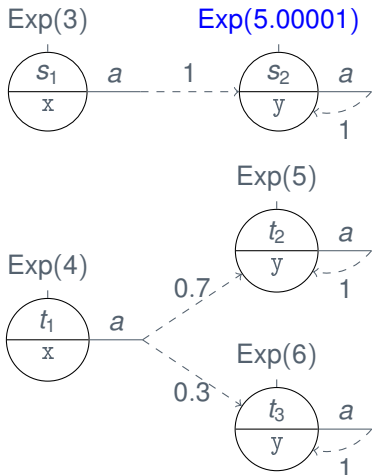


$$s_1 \preceq t_1$$



# Introduction

## Example



$$s_1 \not\sim t_1$$



# Introduction

## Quantitative behavioural relations

Jou and Smolka '90<sup>1</sup>: Pseudometrics rather than equivalences

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<sup>1</sup>Chi-Chang Jou and Scott A. Smolka: Equivalences, congruences, and complete axiomatizations for probabilistic processes, CONCUR 1990



# Introduction

## Quantitative behavioural relations

Jou and Smolka '90<sup>1</sup>: Pseudometrics rather than equivalences

Now: Hemimetrics rather than preorders

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Hemimetric



# Hemimetric Simulation

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We focus on the **real-time** behaviour of systems.

# Hemimetric

A distance on CDFs



$F_2 \sqsubseteq F_1$  iff  $F_1(t) \leq F_2(t)$  for all  $t$  – usual stochastic order

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A distance on CDFs



$F_2 \sqsubseteq F_1$  iff  $F_1(t) \leq F_2(t)$  for all  $t$  – usual stochastic order

$F_2 \sqsubseteq_{\varepsilon} F_1$  iff  $F_1(t) \leq F_2(\varepsilon \cdot t)$  for all  $t$  –  $\varepsilon$ -faster than

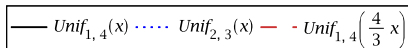
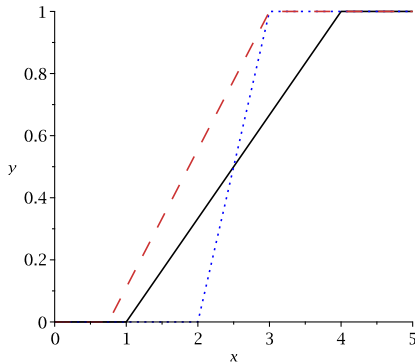




# Hemimetric

## Example

$$\text{Unif}[1, 4] \sqsubseteq_{\frac{4}{3}} \text{Unif}[2, 3]$$





# Hemimetric

$\varepsilon$ -simulation

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$s_1 \preceq_{\varepsilon} s_2$  –  $s_2$   $\varepsilon$ -simulates  $s_1$

# Hemimetric Distance



$$d(s_1, s_2) = \inf\{\varepsilon \geq 1 \mid s_1 \preceq_\varepsilon s_2\}$$

- ▶  $d(s_1, s_2) = 1$  iff  $s_1 \preceq s_2$ .
- ▶  $\log d(s_1, s_2)$  is a hemimetric.

# Hemimetric

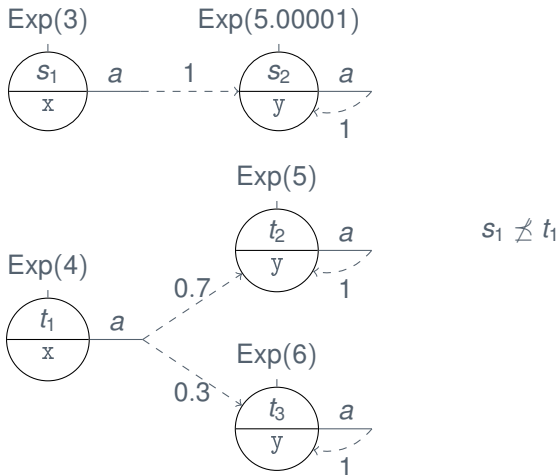
## Intuition



- ▶  $\varepsilon$  is an *acceleration factor*.
- ▶  $s_1 \preceq_\varepsilon s_2$  means that  $s_2$  simulates  $s_1$  if we accelerate the real-time behaviour of  $s_2$  by a factor  $\varepsilon$ .
- ▶  $d(s_1, s_2)$  is the infimum over such acceleration factors.

# Hemimetric

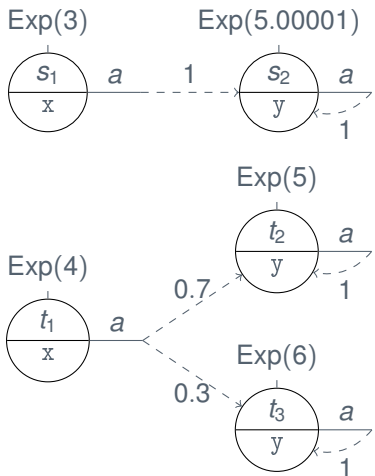
## Example





# Hemimetric

## Example



$$d(s_1, s_2) = \frac{5.00001}{5}$$

$$= 1.000002$$

Computing the distance





# Computing the distance

## Definitions

$$c(F, G) = \inf\{\varepsilon \geq 1 \mid F \sqsubseteq_\varepsilon G\}$$

Note: We have closed-form solutions for  $c(F, G)$  when  $F$  and  $G$  are Dirac, exponential, or uniform.

$$\mathcal{C}(M) = \{c(F_s, F_{s'}) \mid s, s' \in S\}$$



# Computing the distance

The idea

## Lemma

Let  $M$  be a finite SMDP. If  $d(s_1, s_2) \neq \infty$ , then

- ▶  $s_1 \preceq_c s_2$  for some  $c \in \mathcal{C}(M)$  and
- ▶  $d(s_1, s_2) = \min\{c \in \mathcal{C}(M) \mid s_1 \preceq_c s_2\}$ .

The lemma tells us:

- ▶ If there is no  $c \in \mathcal{C}(M)$  such that  $s_1 \preceq_c s_2$ , then  $d(s_1, s_2) = \infty$ .
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$$d(s_1, s_2) = \min\{c \in \mathcal{C}(M) \mid s_1 \preceq_c s_2\}$$

We need to be able to decide whether  $s_1 \preceq_c s_2$ .



# Computing the distance

Deciding  $\varepsilon$ -similarity

We adapt the algorithm from Baier et al.<sup>2</sup> for deciding similarity.

## Theorem

*For finite SMDPs, we can decide whether  $s_1 \preceq_\varepsilon s_2$  in time  $\mathcal{O}(n^2(f(l) + k) + (mn^7)/\log n)$ , where*

- ▶  $n = |S|$  is the number of states,
- ▶  $m = |A|$  is the number of actions,
- ▶  $k = |AP|$  is the number of atomic propositions, and
- ▶  $f(l)$  is the complexity of computing  $c(F, G)$ .

Note:  $f(l)$  is constant when considering Dirac, exponential, and uniform distributions.

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<sup>2</sup>Christel Baier, Bettina Engelen, and Mila E. Majster-Cederbaum: Deciding Bisimilarity and Similarity for Probabilistic Processes, J. Comput. Syst. Sci. 2000



# Computing the distance

## Algorithm

We can now use a bisection method to search through  $c \in \mathcal{C}(M)$  and check whether  $s_1 \preceq_c s_2$ .

```

1 Order the elements of  $\mathcal{C}(M) \setminus \{\infty\}$  such that  $c_1 < c_2 < \dots < c_n$ ;
2 if  $s_1 \preceq_{c_1} s_2$  then return  $c_1$  ;
3 else if  $s_1 \not\preceq_{c_n} s_2$  then return  $\infty$  ;
4 else
5      $i \leftarrow 1, j \leftarrow n$ ;
6     while  $i < j$  do
7          $h \leftarrow \lceil \frac{j-i}{2} \rceil$ ;
8         if  $s_1 \preceq_{c_{j-h}} s_2$  then  $j \leftarrow j - h$  ;
9         else  $i \leftarrow i + h$  ;
10    end
11    return  $c_j$ ;
12 end

```



# Computing the distance

## Complexity

Since the bisection method halves the number of remaining elements in each step, it iterates at most  $\log n$  times.

### Theorem

*The simulation distance can be computed in time  $\mathcal{O}(n^2(f(l) + k) + mn^7)$ .*

# Compositionality



# Compositionality

## Composing SMDPs

### Definition

$M_1 \parallel_{\star} M_2$  is given by

- ▶  $S = S_1 \times S_2$ ,
- ▶  $\tau((s_1, s_2), a)((s'_1, s'_2)) = \tau_1(s_1, a)(s'_1) \cdot \tau_2(s_2, a)(s'_2)$ ,
- ▶  $\rho((s_1, s_2)) = \star(\rho(s_1), \rho(s_2))$ , and
- ▶  $L((s_1, s_2)) = L(s_1) \cup L(s_2)$ .

$\star$  is a function for composing real-time behaviour.





# Compositionality

## Composing SMDPs

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- ▶  $L((s_1, s_2)) = L(s_1) \cup L(s_2)$ .

$\star$  is a function for composing real-time behaviour.

- ▶ Maximum composition:  $F_{\star(\mu, \nu)}(t) = \max(F_\mu(t), F_\nu(t))$ .
- ▶ Product rate composition:  $F_{\star(\mu, \nu)}(t) = \text{Exp}[\theta \cdot \theta'](t)$ .
- ▶ Minimum rate composition:  $F_{\star(\mu, \nu)}(t) = \text{Exp}[\min(\theta, \theta')](t)$ .
- ▶ Maximum rate composition:  $F_{\star(\mu, \nu)}(t) = \text{Exp}[\max(\theta, \theta')](t)$ .



# Compositionality

## Non-expansiveness

### Definition

$\star$  is *monotonic* if  $F_\mu \sqsubseteq_\varepsilon F_\nu$  implies  $F_{\star(\mu,\eta)} \sqsubseteq_\varepsilon F_{\star(\nu,\eta)}$ .

### Theorem

*For finite SMDPs and monotonic  $\star$ ,*

$$d(s_1, s_2) \leq \varepsilon \quad \text{implies} \quad d(s_1 \parallel_\star s_3, s_2 \parallel_\star s_3) \leq \varepsilon.$$

Logic

# Logic

## Timed Markovian Logic



TML :  $\varphi, \varphi' ::= \alpha \mid \neg\alpha \mid \ell_p t \mid m_p t \mid L_p^a \varphi \mid M_p^a \varphi \mid \varphi \wedge \varphi' \mid \varphi \vee \varphi'$



# Logic

## Timed Markovian Logic

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|                                     |     |  |                           |     |  |
|-------------------------------------|-----|--|---------------------------|-----|--|
| $s \models \alpha$                  | iff | $\alpha \in L(s)$                            | $s \models \ell_p t$      | iff | $F_s(t) \geq p$                                    |
| $s \models \neg\alpha$              | iff | $\alpha \notin L(s)$                         | $s \models m_p t$         | iff | $F_s(t) \leq p$                                    |
| $s \models \varphi \wedge \varphi'$ | iff | $s \models \varphi$ and $s \models \varphi'$ | $s \models L_p^a \varphi$ | iff | $\tau(s, a)(\llbracket \varphi \rrbracket) \geq p$ |
| $s \models \varphi \vee \varphi'$   | iff | $s \models \varphi$ or $s \models \varphi'$  | $s \models M_p^a \varphi$ | iff | $\tau(s, a)(\llbracket \varphi \rrbracket) \leq p$ |



# Logic

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$\text{TML}^{\geq}$  :  $\varphi ::= \alpha \mid \neg\alpha \mid \ell_p t \mid L_p^a \varphi \mid \varphi \wedge \varphi' \mid \varphi \vee \varphi'$

$\text{TML}^{\leq}$  :  $\varphi ::= \alpha \mid \neg\alpha \mid m_p t \mid M_p^a \varphi \mid \varphi \wedge \varphi' \mid \varphi \vee \varphi'$



# Logic

$\varepsilon$ -perturbation

$(\varphi)_\varepsilon$  is defined inductively as

$$(\alpha)_\varepsilon = \alpha$$

$$(\neg\alpha)_\varepsilon = \neg\alpha$$

$$(\varphi \wedge \varphi')_\varepsilon = (\varphi)_\varepsilon \wedge (\varphi')_\varepsilon$$

$$(\varphi \vee \varphi')_\varepsilon = (\varphi)_\varepsilon \vee (\varphi')_\varepsilon$$

$$(\ell_p t)_\varepsilon = \ell_p \varepsilon \cdot t$$

$$(m_p t)_\varepsilon = m_p \varepsilon \cdot t$$

$$(L_p^a \varphi)_\varepsilon = L_p^a (\varphi)_\varepsilon$$

$$(M_p^a \varphi)_\varepsilon = M_p^a (\varphi)_\varepsilon$$



# Logic

## Logical characterisation

### Theorem

*For finite SMDPs the following holds.*

- ▶  $d(s_1, s_2) \leq \varepsilon$  if and only if  $\forall \varphi \in \text{TML}^{\geq}. s_1 \models \varphi \implies s_2 \models (\varphi)_{\varepsilon}$ .
- ▶  $d(s_1, s_2) \leq \varepsilon$  if and only if  $\forall \varphi \in \text{TML}^{\leq}. s_2 \models \varphi \implies s_1 \models (\varphi)_{\varepsilon}$ .





# Logic

## Logical characterisation

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*For finite SMDPs the following holds.*

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### Corollary

*For finite SMDPs we have*

$$s_1 \sim s_2 \text{ if and only if } \forall \varphi \in \text{TML}. s_1 \models \varphi \iff s_2 \models \varphi.$$

## Conclusion



# Conclusion

## Summary

- ▶ We have introduced a quantitative  $\varepsilon$ -simulation relation for SMDPs based on the usual stochastic order.
- ▶  $\varepsilon$ -simulation induces a (multiplicative) hemimetric.
- ▶ The hemimetric is computable – polynomial time for Dirac, exponential, and uniform distributions.
- ▶ Parallel composition is non-expansive w.r.t. the hemimetric.
- ▶ The distance is characterised by a timed extension of Markovian logic.



# Conclusion

## Open Problems

- ▶ What about infinite systems?
- ▶ Computing  $c(F, G) = \inf\{\varepsilon \geq 1 \mid F \sqsubseteq_\varepsilon G\}$  for composition.
  - ▶ E.g. uniform distributions are not closed under composition.
- ▶ Topological properties of the hemimetric?



# Conclusion

## Question

- ▶ **Simulation:** for all  $a \in A$  there exists a coupling  $\Delta_a: \mathcal{S} \times \mathcal{S} \rightarrow [0, 1]$  between  $\tau(s_1, a)$  and  $\tau(s_2, a)$  such that
  - ▶  $\Delta_a(s, s') > 0$  implies  $(s, s') \in R$ ,
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  - ▶  $\tau(s_2, a)(s') = \sum_{s \in \mathcal{S}} \Delta_a(s, s')$  for all  $s' \in \mathcal{S}$ .
- ▶ **Simulation (alternative):** for all  $a \in A$  and  $C \subseteq \mathcal{S}$ ,  $\tau(s_1, a)(C) \leq \tau(s_2, a)(R(C))$ .

The two definitions are equivalent for *finite* SMDPs<sup>3</sup>.

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<sup>3</sup>Lijun Zhang: Decision algorithms for probabilistic simulations, PhD thesis, Saarland University 2009



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**Question:** What about *infinite* SMDPs?

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