

Playing Games with Metrics

Uli Fahrenberg Claus Thrane Kim G. Larsen

CS @ Aalborg

Maths @ Aalborg seminar
Nov. 2010

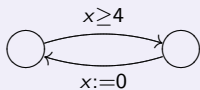
1 Background: Quantitative analysis

2 Weighted automata and traces

3 Linear vs. branching distance

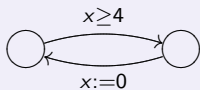
Quantitative Analysis

Quantitative Models



Quantitative Quantitative Analysis

Quantitative Models

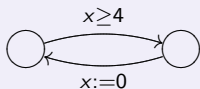


Quantitative Logics

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

Quantitative Quantitative Quantitative Analysis

Quantitative Models



Quantitative Logics

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

Quantitative Verification

$$\begin{aligned} \llbracket \varphi \rrbracket (s) &= 3.14 \\ d(s, t) &= 42 \end{aligned}$$

Boolean world

Trace equivalence \equiv

Bisimilarity \sim

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

“Quantification”

Linear distance d_L

Branching distance d_B

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

Weighted Automata and Traces

Definition

A **weighted automaton**: states S , transitions $T \subseteq S \times \mathbb{K} \times S$

- \mathbb{K} : Set of **weights**.
- Standard example: $\mathbb{K} = L \times \mathbb{R}$. Discrete labels L , real weights \mathbb{R} .

Definition

A **trace** is an infinite sequence of weights; an element of \mathbb{K}^ω .

- Notation: For $s \in S$ in a weighted automaton (S, T) , $\text{Tr}(s)$ is the set of **traces from s** .

Framework for Quantitative Analysis

Trace distance

Assume given a **hemimetric** $d_T : \mathbb{K}^\omega \times \mathbb{K}^\omega \rightarrow [0, \infty]$.

That's it. We only assume some way to measure distance between traces.

- Think of the trace distance as **application defined**
- May or may not come from some metric on \mathbb{K}

(Hemimetric: not necessarily symmetric pseudometric:

- $d_T(x, x) = 0$ (indiscernibility of identicals)
- $d_T(x, y) + d_T(y, z) \geq d_T(x, z)$ (triangle inequality))

Examples of Trace Distances

- Let $\mathbb{K} = L \times \mathbb{R}$. Notation: Trace $\sigma = ((\sigma_0^l, \sigma_0^w), (\sigma_1^l, \sigma_1^w), \dots)$.

Point-wise trace distance

$$d_T^\bullet(\sigma, \tau) = \begin{cases} \sup_i |\sigma_i^w - \tau_i^w| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Accumulating trace distance

$$d_T^+(\sigma, \tau) = \begin{cases} \sum_i |\sigma_i^w - \tau_i^w| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Maximum-lead trace distance

$$d_T^\pm(\sigma, \tau) = \begin{cases} \sup_i \left| \sum_{j=0}^i \sigma_j^w - \sum_{j=0}^i \tau_j^w \right| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Examples of Trace Distances

- Let $\mathbb{K} = L \times \mathbb{R}$. Notation: Trace $\sigma = ((\sigma_0^l, \sigma_0^w), (\sigma_1^l, \sigma_1^w), \dots)$.

Point-wise trace distance

$$d_T^\bullet(\sigma, \tau) = \begin{cases} \sup_i \lambda^i |\sigma_i^w - \tau_i^w| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Accumulating trace distance

$$d_T^+(\sigma, \tau) = \begin{cases} \sum_i \lambda^i |\sigma_i^w - \tau_i^w| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Maximum-lead trace distance

$$d_T^\pm(\sigma, \tau) = \begin{cases} \sup_i |\sum_{j=0}^i \sigma_j^w - \sum_{j=0}^i \tau_j^w| & \text{if } \sigma_i^l = \tau_i^l \text{ for all } i \\ \infty & \text{otherwise} \end{cases}$$

Linear Distance

- (Recall: We assume given a hemimetric $d_T : \mathbb{K}^\omega \times \mathbb{K}^\omega \rightarrow [0, \infty]$ on traces.)
- Let $(S, T \subseteq S \times \mathbb{K} \times S)$ be a weighted automaton.
- Linear distance between states $s, t \in S$: use **Hausdorff construction**:

Definition: Linear distance

$$d_L(s, t) = \sup_{\sigma \in \text{Tr}(s)} \inf_{\tau \in \text{Tr}(t)} d_T(\sigma, \tau)$$

Linear vs. Branching Distance

Definition: Linear distance

$$d_L(s, t) = \sup_{\sigma \in \text{Tr}(s)} \inf_{\tau \in \text{Tr}(t)} d_T(\sigma, \tau)$$

- This is a game!
- Player 1 chooses the worst trace $\sigma \in \text{Tr}(s)$.
- Player 2 matches it with the best trace $\tau \in \text{Tr}(t)$.
- $d_L(s, t)$ = value of the “1-blind weighted simulation game”: Player 2 has perfect information, **Player 1 is blind**.

Definition: Branching distance

$d_B(s, t)$ = value of the same game, **but with perfect information**

- Hence “ $d_B(s, t) = \sup_{s \xrightarrow{\sigma_0} s_1} \inf_{t \xrightarrow{\tau_0} t_1} \sup_{s_1 \xrightarrow{\sigma_1} s_2} \inf_{t_1 \xrightarrow{\tau_1} t_2} \dots d_T(\sigma, \tau)$ ”.

Simulation Games

Precise definition of how this works:

- Given: Weighted automaton $(S, T \subseteq S \times \mathbb{K} \times S)$, states $s, t \in S$
- (Imagine a game of two players taking turns to build two paths:)
- A **strategy** from s, t : $\theta : \text{fPa}(s) \times \text{fPa}(t) \rightarrow T$
 - for Player 1: $\text{start}(\theta(\pi_1, \pi_2)) = \text{end}(\pi_1)$
 - for Player 2: $\text{start}(\theta(\pi_1, \pi_2)) = \text{end}(\pi_2)$
- A **round** of the game under strategies θ_1, θ_2 :
 $\text{Round}_{(\theta_1, \theta_2)}(\pi_1, \pi_2) = (\pi_1 \cdot \theta_1(\pi_1, \pi_2), \pi_2 \cdot \theta_2(\pi_1 \cdot \theta_1(\pi_1, \pi_2), \pi_2))$
- The **limit** of the game under strategies θ_1, θ_2 :
 $\lim_{j \rightarrow \infty} \text{Round}_{(\theta_1, \theta_2)}^j(s_0, t_0)$ (a pair of infinite paths)
- The **utility** of the strategies θ_1, θ_2 :
 $u(\theta_1, \theta_2) = d_T(\text{tr}(\lim_{j \rightarrow \infty} \text{Round}_{(\theta_1, \theta_2)}^j(s_0, t_0)))$
- The **value** of the game: $v(s, t) = \sup_{\theta_1} \inf_{\theta_2} u(\theta_1, \theta_2)$

Perfect vs. Imperfect Information

- $\Theta_1(s, t), \Theta_2(s, t)$: sets of **all** Player-1 resp. Player-2 strategies
 $\text{fPa}(s) \times \text{fPa}(t) \rightarrow T$
- Games with **imperfect information**: Restrict available strategies to proper subsets of Θ_1 or Θ_2
- Special case: **blind** Player-1 strategies $\tilde{\Theta}_1 = T^{\text{fPa}(s)}$
- Do not depend on Player-2 choices: Player 1 cannot “see” what Player 2 is doing
- **Branching** distance: $d_B(s, t) = \sup_{\theta_1 \in \Theta_1(s, t)} \inf_{\theta_2 \in \Theta_2(s, t)} u(\theta_1, \theta_2)$
- **Linear** distance: $d_L(s, t) = \sup_{\theta_1 \in \tilde{\Theta}_1(s, t)} \inf_{\theta_2 \in \Theta_2(s, t)} u(\theta_1, \theta_2)$

Properties

Proposition

- d_L is a hemimetric.
- If the simulation game is *determined*, d_B is a hemimetric.

- Need determinacy to show triangle inequality
- (But have no counterexample)

Theorem

For all $s, t \in S$, $d_L(s, t) \leq d_B(s, t)$.

Proof:

For d_B , Player 1 (the *sup* player) has more strategies to choose from!

Properties

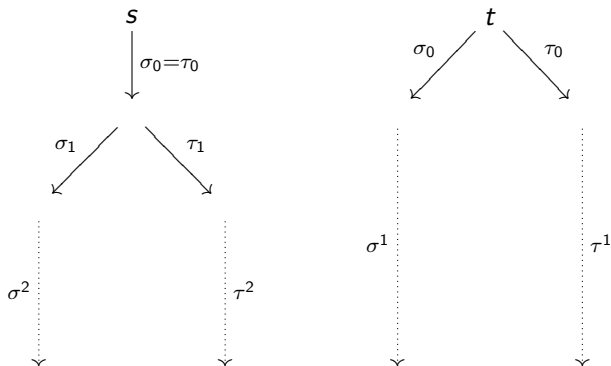
Theorem

*There exists a weighted automaton on which d_L and d_B are **topologically inequivalent**.*

- Unless for all traces $\sigma, \tau : \sigma_0 = \tau_0$ implies $d_T(\sigma, \tau) = 0$.
- (i.e. d_T measures only on *first* trace element; not very useful!)

Proof

Let $\sigma, \tau \in \mathbb{K}^\omega$ such that $\sigma_0 = \tau_0$, $d_T(\sigma, \tau) > 0$, and $d_T(\tau, \sigma) > 0$.



We have $\text{Tr}(s) = \text{Tr}(t)$, hence $d_L(s, t) = 0$. On the other hand, $d_B(s, t) = \min(d_T(\sigma, \tau), d_T(\tau, \sigma)) > 0$. That's it.

Wish List

- Relate equivalence of trace distances to equivalence of linear distances. Like this:

Theorem

If trace distances d_T^1 and d_T^2 are *Lipschitz equivalent*, then the corresponding linear distances d_L^1 and d_L^2 are *topologically equivalent*.

- Relate equivalence of trace distances to equivalence of branching distances.
- Classify trace distances (up to equivalence).