

Bisimulation Metrics for Weighted Automata

B. Balle^{1,*}, *P. Gourdeau*² and P. Panangaden²

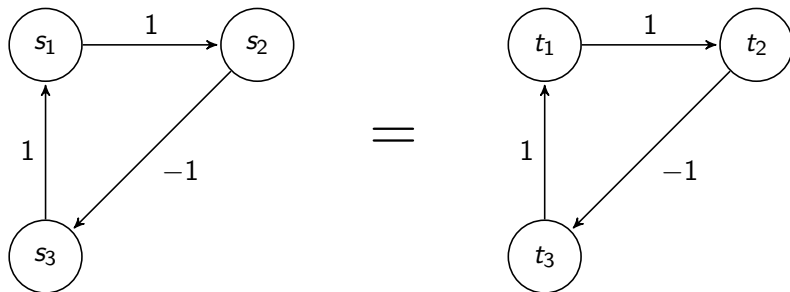
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^{*}(work done while at Lancaster University)

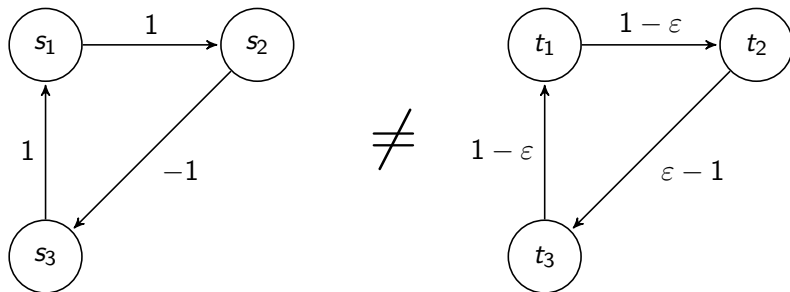
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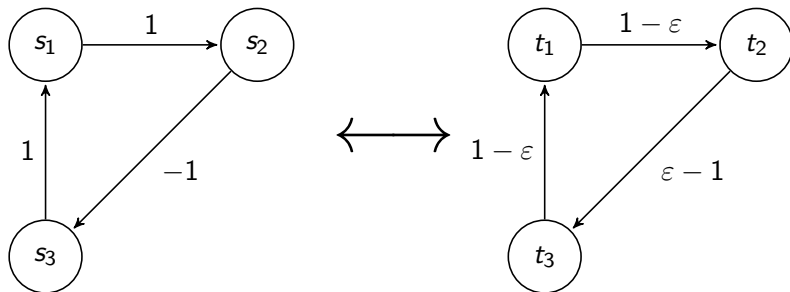
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- 3 We show two continuity properties of the metric; one using definitions due to Jaeger et al. and the other developed here.
- 4 We show undecidability results for computing our metrics.
- 5 Nevertheless, we show that one can successfully exploit these metrics for applications in spectral learning.
- 6 Bisimulation for pseudometrics were first defined for LMPs in 1999 by Desharnais, Gupta, Jagadeesan and Panangaden and have been studied and developed for other models since then.

Weighted Finite Automata

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- Σ is a finite alphabet,
- V is a finite-dimensional vector space,
- $\alpha \in V$ is a vector representing the initial weights,
- $\beta \in V^*$ is a linear form representing the final weights,
- $\tau_\sigma : V \rightarrow V$ is a linear map representing the transition indexed by $\sigma \in \Sigma$.

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Given a word $x = x_1 \dots x_n \in \Sigma^*$, the automaton \mathcal{A} realizes the function $f_{\mathcal{A}} : \Sigma^* \rightarrow \mathbb{R}$ defined by

$$f_{\mathcal{A}}(x) = \beta(\tau_{x_n}(\dots \tau_{x_1}(\alpha))) = \beta(\tau_x(\alpha)) .$$

Weighted Finite Automata

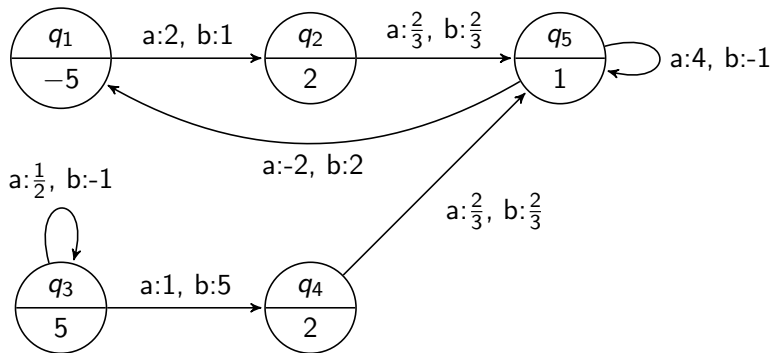


Figure 1: An example of a WFA where $V = \mathbb{R}^5$ (with the standard basis) and $\Sigma = \{a, b\}$. The final weights of the states are in the lower half of the circles and the initial weights are omitted.

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For every WFA \mathcal{A} there exists a largest linear bisimulation $W_{\mathcal{A}}$ for \mathcal{A} such that $\sim_{\mathcal{A}} \equiv \sim_{W_{\mathcal{A}}}$.

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We want a *quantitative analogue* of this relation.

Bisimulation

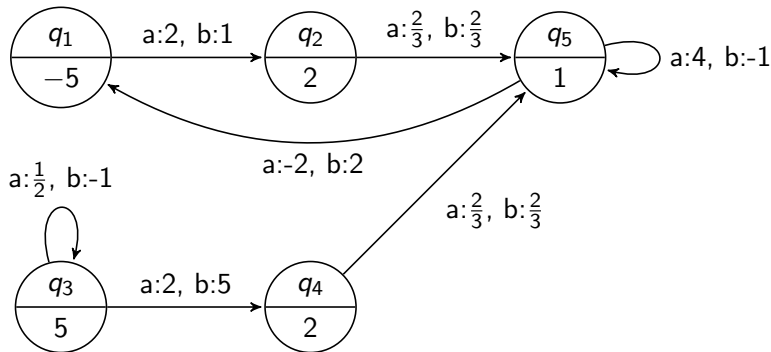


Figure 2: Here a linear bisimulation would be $W = \{(0 \ \lambda \ 0 \ -\lambda \ 0)^T : \lambda \in \mathbb{R}\}$.

Framework

S : set of all seminorms on V .

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WFA \mathcal{A} with

$\gamma > 0$ and $\rho(\mathcal{A})\gamma < 1$

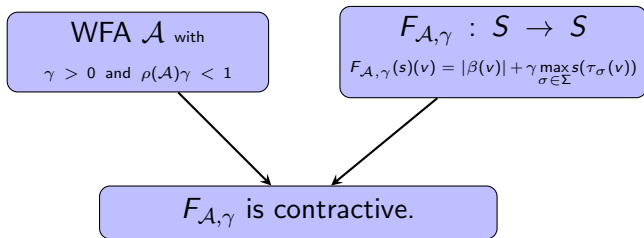
$F_{\mathcal{A},\gamma} : S \rightarrow S$

$F_{\mathcal{A},\gamma}(s)(v) = |\beta(v)| + \gamma \max_{\sigma \in \Sigma} s(\tau_{\sigma}(v))$

$\rho(\mathcal{A})$: joint spectral radius of the transition maps $\{\tau_{\sigma}\}_{\sigma \in \Sigma}$.

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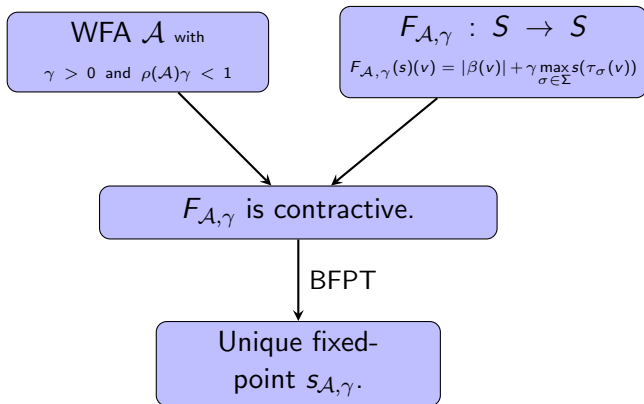
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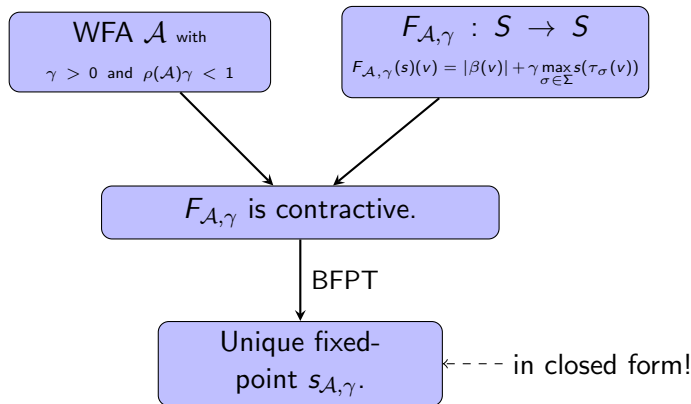
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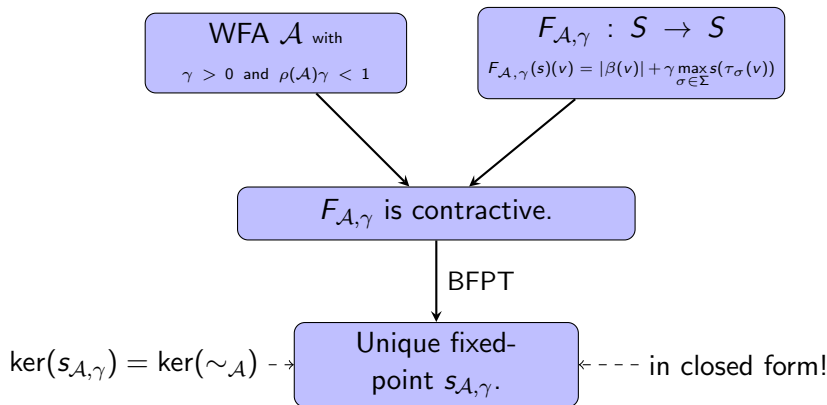
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Definition (Difference automaton)

Let \mathcal{A}_1 and \mathcal{A}_2 be two weighted automata over the same finite alphabet Σ . Define their *difference automaton* as

$\mathcal{A} = \mathcal{A}_1 - \mathcal{A}_2 = \langle \Sigma, V, \alpha, \beta, \{\tau_\sigma\}_{\sigma \in \Sigma} \rangle$ where $V = V_1 \oplus V_2$, $\alpha = \alpha_1 \oplus (-\alpha_2)$, $\beta = \beta_1 \oplus \beta_2$, and $\tau_\sigma = \tau_{1,\sigma} \oplus \tau_{2,\sigma}$ for all $\sigma \in \Sigma$.

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Definition

Let \mathcal{A}_1 and \mathcal{A}_2 be two weighted automata and let \mathcal{A} be their difference automaton. For any $\gamma < 1/\rho(\mathcal{A})$ we define the γ -bisimulation distance between \mathcal{A}_1 and \mathcal{A}_2 as $d_\gamma(\mathcal{A}_1, \mathcal{A}_2) = s_{\mathcal{A},\gamma}(\alpha)$.

Proposition

Let \mathcal{A}_1 and \mathcal{A}_2 two weighted automata and $\gamma < 1/\max\{\rho(\mathcal{A}_1), \rho(\mathcal{A}_2)\}$. Then $d_\gamma(\mathcal{A}_1, \mathcal{A}_2)$ satisfies $d_\gamma(\mathcal{A}_1, \mathcal{A}_2) = 0$ if and only if $f_{\mathcal{A}_1} = f_{\mathcal{A}_2}$.

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- An upper bound on the behavioural distance between two systems should imply an upper bound on the difference of their outputs as a function of the length of the input string. (*Input Continuity*)
- Inspired by the continuity properties for labelled Markov chains presented by Jaeger et. al (2014).

Definition

Let $(\mathcal{A}_i)_{i \in \mathbb{N}}$ be a sequence of WFA $\mathcal{A}_i = \langle \Sigma, V, \alpha_i, \beta_i, \{\tau_{i,\sigma}\}_{\sigma \in \Sigma} \rangle$ over the same alphabet Σ and normed vector space $(V, \|\cdot\|)$. We say that the sequence (\mathcal{A}_i) *converges* to $\mathcal{A} = \langle \Sigma, V, \alpha, \beta, \{\tau_\sigma\}_{\sigma \in \Sigma} \rangle$ if

- $\lim_{i \rightarrow \infty} \|\alpha_i - \alpha\| = 0$,
- $\lim_{i \rightarrow \infty} \|\beta_i - \beta\|_* = 0$,
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Definition

A pseudometric d between weighted automata is *parameter continuous* if for any sequence $(\mathcal{A}_i)_{i \in \mathbb{N}}$ converging to some weighted automaton \mathcal{A} , $\lim_{i \rightarrow \infty} d(\mathcal{A}, \mathcal{A}_i) = 0$.

Theorem

The γ -bisimulation distance between weighted automata is parameter continuous for any sequence of weighted automata $(\mathcal{A}_i)_{i \in \mathbb{N}}$ converging to a weighted automaton \mathcal{A} with $\gamma < 1/\rho(\mathcal{A})$.

Computing the Pseudometric

- Closed form expression for the seminorm:

$$s_{\mathcal{A},\gamma}(v) = \sup_{x \in \Sigma^\infty} \sum_{t=0}^{\infty} \gamma^t |\beta(\tau_{x_{\leq t}}(v))| = \sup_{x \in \Sigma^\infty} \sum_{t=0}^{\infty} \gamma^t |f_{\mathcal{A}_v}(x_{\leq t})| ,$$

and for the pseudometric:

$$d_\gamma(\mathcal{A}_1, \mathcal{A}_2) = \sup_{x \in \Sigma^\infty} \sum_{t=0}^{\infty} \gamma^t |f_{\mathcal{A}_1}(x_{\leq t}) - f_{\mathcal{A}_2}(x_{\leq t})| .$$

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- Supremum over all infinite strings and absolute value: looks hard to compute.

Undecidability Result

Theorem

The following problem is undecidable: given a weighted automaton $\mathcal{A} = \langle \Sigma, V, \alpha, \beta, \{\tau_\sigma\}_{\sigma \in \Sigma} \rangle$, a discount factor $\gamma < 1/\rho(\mathcal{A})$, and a threshold $\nu > 0$, decide whether $s_{\mathcal{A}, \gamma}(\alpha) > \nu$.

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Proof idea: Reduction from computing the value function of unobservable MDPs (special cases of POMDPs) in a discounted infinite-horizon setting.

- Despite the undecidability result, it is possible to bound the error of some algorithms in terms of the pseudometric to analyse their output.

Spectral Learning Applications

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 - Previous results all use ℓ_1 distance on strings of bounded length, which is weaker.
 - Proof idea: we combine continuity properties of pseudometric and continuity properties of joint spectral radius – this involves some delicate technical bounds.

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- Satisfies parameter continuity and input continuity properties (under certain assumptions).
- Applications to spectral learning.
- Future work: develop an algorithm to approximately compute the bisimulation pseudometrics.
 - Will most likely rely on the sum-of-squares programming approximation algorithm to compute the JSR of a set of matrices.

Thank you!

Definition

The *joint spectral radius* of a collection $M = \{\tau_i\}_{i \in I}$ of linear maps $\tau_i : V \rightarrow V$ on a normed vector space $(V, \|\cdot\|)$ is defined as

$$\rho(M) = \limsup_{t \rightarrow \infty} \left(\sup_{T \in I^t} \left\| \prod_{i \in T} \tau_i \right\| \right)^{1/t} = \lim_{t \rightarrow \infty} \left(\sup_{T \in I^t} \left\| \prod_{i \in T} \tau_i \right\| \right)^{1/t} .$$

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The joint spectral radius of \mathcal{A} , denoted as $\rho(\mathcal{A})$ is defined as $\rho(\{\tau_\sigma\}_{\sigma \in \Sigma})$ and can be rewritten as:

$$\rho(\mathcal{A}) = \lim_{t \rightarrow \infty} \left(\sup_{x \in \Sigma^t} \|\tau_x\| \right)^{1/t}.$$

Appendix – Metric for Banach's Fixed-Point Theorem

We define the following metric d on S :

$$d(s, s') = \sup_{\|v\| \leq 1} |s(v) - s'(v)| ,$$

where $\|\cdot\|$ is the following norm:

Theorem (Rota 1960)

Let $M = \{\tau_i\}_{i \in I}$ be a compact set of linear maps on V . For any $\eta > 0$ there exists a norm $\|\cdot\|$ on V that satisfies $\|\tau_i(v)\| \leq (\rho(M) + \eta) \|v\|$ for every $i \in I$ and every $v \in V$.

Appendix – Closed form

- Let $\mathcal{A} = \langle \Sigma, V, \alpha, \beta, \{\tau_\sigma\}_{\sigma \in \Sigma} \rangle$.
- $\gamma < 1/\rho(\mathcal{A})$.
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Theorem

Let $s_{\mathcal{A},\gamma} \in \mathcal{S}$ be the fixed point of $F_{\mathcal{A},\gamma}$. Then for any $v \in V$ we have

$$s_{\mathcal{A},\gamma}(v) = \sup_{x \in \Sigma^\infty} \sum_{t=0}^{\infty} \gamma^t |\beta(\tau_{x_{\leq t}}(v))| = \sup_{x \in \Sigma^\infty} \sum_{t=0}^{\infty} \gamma^t |f_{\mathcal{A}_v}(x_{\leq t})| .$$

Theorem (Theorem 4.4 in Madani03)

The following problem is undecidable: given a UMDP \mathcal{U} and a threshold ν decide whether there exists a sequence of actions $x \in \Sigma^\infty$ such that $V_{\mathcal{U}}(x) > \nu$.

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Corollary

The problem in the previous theorem remains undecidable when restricted to UMDP with non-negative action-independent rewards.