# Behavioural Metrics via Functor Lifting – A Coalgebraic Approach

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#### Overview

- 1 Motivation: Behavioural Equivalences and Metrics
- 2 Examples: Metric and Probabilistic Transition Systems
- 3 Coalgebra: A General Framework for Transition Systems
- 4 Coalgebras and Behavioural Metrics
- 5 Compositionality & Up-To Techniques

# Behavioural Equivalences

In the analysis of state-based systems, behavioural equivalences (bisimilarity, trace equivalence, ...) relate states with the same behaviour.

#### **Applications**

- Comparing a system with its specification
- Minimizing the state space
- Analysis of model transformations
- Verification of cryptographic protocols (are two protocols equivalent from the point of view of an external observer, a.k.a. the attacker?)

## Behavioural Equivalences

This talk: bisimilarity (and generalizations thereof ...)

#### Bisimulation

Let L be a set of labels and let X be a set of states with transition relation  $\rightarrow \subseteq X \times L \times X$  (written  $x \stackrel{a}{\rightarrow} x'$ ).

A symmetric relation  $R \subseteq X \times X$  is a bisimulation if for all pairs  $(x,y) \in R$  and all states x' with  $x \stackrel{a}{\to} x'$ , there exists a state y' with  $y \stackrel{a}{\to} y'$  and  $(x',y') \in R$ .

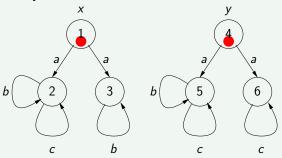
Two states x, y are bisimilar whenever there exists a bisimulation R with  $(x, y) \in R$  (written  $x \sim y$ ).

## Behavioural Equivalences

#### Characterization as a two-player game

Two tokens on states x, y – Player I (the attacker) chooses a token and makes a move – Player II (the defender) has to find an answer with the other token – If no answer is possible, Player I wins

Two states are equivalent if and only if there is no winning strategy for Player I.



#### Behavioural Metrics

Finding a quantitative notion of behavioural equivalence . . .

- Do not insist on the exact same behaviour.
- Measure the behavioural distance between two states.
- Make statements such as "the behaviour of two states differs only by  $\varepsilon$ ".

 $\rightarrow$  behavioural metrics

## Behavioural Metrics

#### Pseudo-metric space

Let X be a set. A pseudo-metric is a function  $d: X \times X \to [0,1]$  where for all  $x, y, z \in X$ :

- d(x,x) = 0 (identity) (metric if  $(d(x,y) = 0 \Rightarrow x = y)$ )
- d(x,y) = d(y,x) (symmetry)
- $d(x,z) \le d(x,y) + d(y,z)$  (triangle inequality)

A (pseudo-)metric space is a pair (X, d) where X is a set and d is a (pseudo-)metric on X.

## Behavioural Metrics

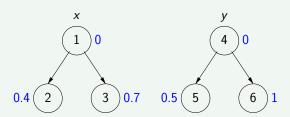
#### Non-expansive function

A non-expansive function  $f: X \to Y$  between two (pseudo-)metric spaces  $(X, d_X), (Y, d_Y)$  satisfies for  $x, y \in X$ 

$$d_X(x,y) \ge d_Y(f(x),f(y))$$

Note: the theory can be generalized to quantales (reversing the order).

Metric transition system [de Alfaro et al., 2009] (slightly simplified) Let  $(M, d_r)$  be a metric space. A metric transition system is a tuple  $(X, \tau, [\cdot])$ , where X is a set of states,  $\tau \subseteq X \times X$  is a transition relation and every state x is assigned an element  $[x] \in M$ .



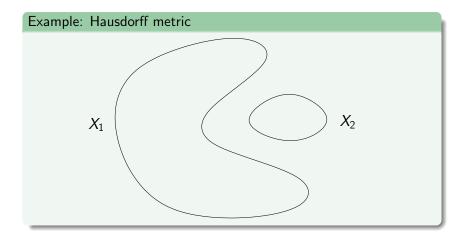
Metric space X = [0, 1] with Euclidean metric.

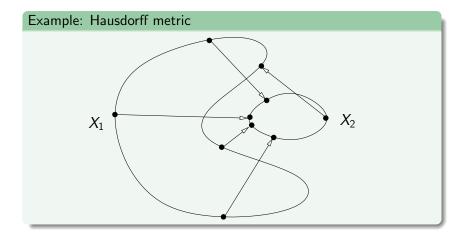
## Hausdorff metric (metric on finite sets)

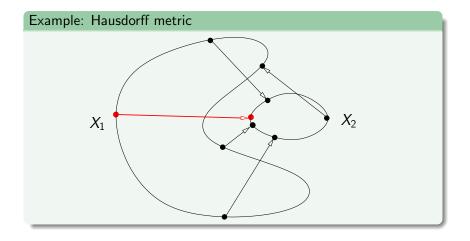
Lifting a metric space (X, d) to  $(\mathcal{P}_{fin}X, d')$ : for  $X_1, X_2 \subseteq X$ :

$$d^{H}(X_{1}, X_{2}) = \max \{ \max_{x \in X_{1}} \min_{y \in X_{2}} d(x, y), \max_{y \in X_{2}} \min_{x \in X_{1}} d(x, y) \}$$

- For each element x (in  $X_1, X_2$ ) take the closest element y in the other set and measure the distance d(x, y)
- Take the maximum of all such distances.



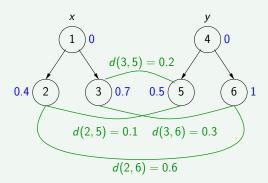




#### Distance of states in a metric transition system

Compute the smallest fixed-point of

$$d(x,y) = \max\{ d_r([x],[y]), d^H(\tau(x),\tau(y)) \}$$

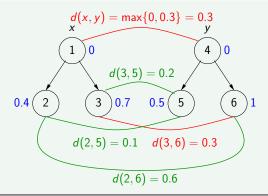


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#### Distance of states in a metric transition system

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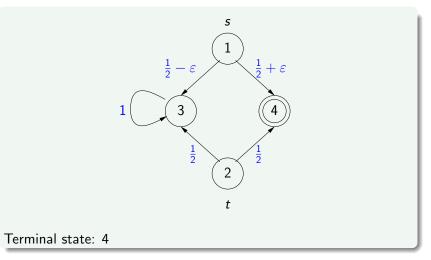
## Probabilistic Transition Systems

#### Probabilistic transition system

A probabilistic transition system is a tuple (X, T, p), where X is a set of states,  $T \subseteq X$  is the set of terminal states and every state  $x \notin T$  is assigned a probability distribution  $p_X \colon X \to [0, 1]$ .

Studied by Larsen/Skou [Larsen and Skou, 1989], van Breugel/Worrell [van Breugel and Worrell, 2005] (again simplified)

# Probabilistic Transition Systems



What is the distance between states 1 and 2?  $\rightarrow$  distance  $\varepsilon$ 

## Probabilistic Transition Systems

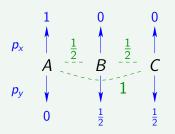
#### Distance of states in a probabilistic transition system

Compute the smallest fixed-point of

$$d(x,y) = \begin{cases} 1 & \text{if } x \in T, y \notin T \text{ or } x \notin T, y \in T \\ 0 & \text{if } x, y \in T \\ d^{P}(p_{x}, p_{y}) & \text{otherwise} \end{cases}$$

What does it mean to compute the distance between two probability distributions  $p_x$ ,  $p_y$  on a metric space?

#### Lift metric to prob. distr.



distances between states probabilities of states

Interpret  $p_x$  as supply and  $p_y$  as demand. Transporting a unit along a distance d costs d.

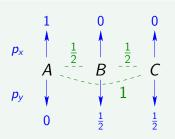
What is the minimal possible cost for transporting supply to demand?

- transport  $\frac{1}{2}$  from A to B: cost  $\frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4}$
- transport  $\frac{1}{2}$  from A to C: cost  $1 \cdot \frac{1}{2} = \frac{1}{2}$

Overall cost:  $\frac{3}{4}$  (= distance  $d^P(p_x, p_y)$ )

# Transportation Problem & Duality [Villani, 2009]

Alternative: you have a logistics firm and handle transportation. You do this by setting a price (per unit) for locations A, B, C  $(pr_A, pr_B, pr_C)$ . You buy and sell for this price at every location. Your prices have to satisfy:  $pr_B - pr_A \le d(A, B)$  (otherwise you do not get the contract).



distances between states probabilities of states

You want to maximize your profit. Which prices do you set?  $\rightarrow pr_A = 0$ ,  $pr_B = \frac{1}{2}$ ,  $pr_C = 1$ 

• you get: 
$$\frac{1}{2} \cdot \frac{1}{2} + 1 \cdot \frac{1}{2} = \frac{3}{4}$$

• you pay: 
$$0 \cdot 1 = 0$$

Profit:  $\frac{3}{4}$ 

# Transportation Problem & Duality [Villani, 2009]

#### Duality in transportation theory (Kantorovich-Rubinstein duality)

The following values coincide for a metric  $d: X \times X \to [0,1]$  and two probability distributions  $p, q: X \to [0,1]$ :

The minimum of 
$$\sum_{x,y} P(x,y) \cdot d(x,y)$$
 for all probability distributions  $P: X \times X \to [0,1]$  (couplings,

indicating transport from x to y), such that  $\sum_{y \in X} P(x, y) = p(x)$ ,  $\sum_{x \in X} P(x, y) = q(y)$  (marginal distributions are p, q)

The maximum of 
$$|\sum_{x \in X} f(x) \cdot p(x) - \sum_{x \in X} f(x) \cdot q(x)|$$
 for all nonexpansive functions  $f: X \to [0,1]$ 

# Generalization of Metric Transition Systems

#### Questions:

- How can we model other types of transition systems (with different branching types)?
- How to set up the fixed-point equation in the general case?
- Are there generic (and efficient) methods to compute metrics?

→ use coalgebra, a general categorical theory of behavioural equivalences, to answer these questions.

Coalgebra offers a toolbox from which transition systems with different branching types can be constructed and analyzed.

#### **Functors**

#### Typical examples of **Set**-endofunctors used for coalgebras

- (finite) powerset functor  $\mathcal{P}_{fin}X = \{Y \mid Y \subseteq X, Y \text{ finite}\}$
- probability distribution functor  $\mathcal{D}X = \{p \colon X \to [0,1] \mid \sum_{x \in X} p(x) = 1\}$
- product functor  $FX = A \times X$  (for a fixed set X)
- coproduct functor (disjoint union) FX = X + B (for a fixed set B)
- combinations of these functors

The functor defines the branching type of the transition system:

- powerset functor → non-determinism
- probability distribution functor → probabilistic branching
- product functor → labelling
- coproduct functor → termination, exceptions, failure

# Coalgebras

Transition systems are now called coalgebras:

#### Coalgebra

Let F be a given functor. A coalgebra is a function  $\gamma \colon X \to FX$  (where X is the state set).

#### Metric transition systems

$$\gamma \colon X \to M \times \mathcal{P}_{fin}X$$

where M is a fixed metric space.

#### Probabilistic transition systems

$$\gamma \colon X \to \mathcal{D}X + 1$$

where 1 is a singleton set  $(1 = {\sqrt})$ , representing termination.

Our (fibrational) approach: [Bonchi et al., 2023]

- Consider a **Set**-coalgebra  $\gamma: X \to FX$ .
- Lift functor on  $F : \mathbf{Set} \to \mathbf{Set}$  to a functor on  $\overline{F} : \mathbf{PMet} \to \mathbf{PMet}$  (transform metric on X to metric on FX)
- Obtain the behavioural metric on X as the least fixpoint of the following map f:

$$\mathsf{PMet}_X \xrightarrow{\overline{F}} \mathsf{PMet}_{FX} \xrightarrow{\gamma^*} \mathsf{PMet}_X$$

where  $\mathbf{PMet}_X$  is the set of pseudo-metrics on X ("fibre" above X) and we use reindexing:

$$\gamma^*(d) = d \circ (\gamma \times \gamma)$$

Needed: general methods for lifting a functor F to metric spaces

→ Wasserstein lifting, Kantorovich lifting

## Evaluation functions and predicate liftings

We need a parameter: an evaluation function (algebra)

$$ev: F[0,1] \rightarrow [0,1]$$

Every evaluation function induces a real-valued predicate lifting:

$$(p: X \rightarrow [0,1]) \mapsto (ev \circ Fp: FX \rightarrow [0,1])$$

#### Notes:

- this can be extended to sets of evaluation maps.
- for the Wasserstein lifting, we have to put some requirements on the evaluation map.

#### Wasserstein lifting

Let  $d: X \times X \rightarrow [0,1]$  be a pseudo-metric and  $t_1, t_2 \in FX$ :

$$d^{\downarrow F}(t_1,t_2) = \inf\{ev(Fd(t)) \mid t \in F(X \times X), F\pi_i(t) = t_i\}$$

$$F(X \times X) \xrightarrow{\langle F\pi_1, F\pi_2 \rangle} FX \times FX \xrightarrow{d^{\downarrow F}} [0, 1]$$

$$\xrightarrow{ev \circ Fd}$$

- View d as a real-valued predicate and lift it.
- For each pair  $(t_1, t_2) \in FX \times FX$  take a coupling in  $F(X \times X)$  that gives the optimal (least) value (direct image).

## Kantorovich lifting (aka codensity lifting [Katsumata, Sato, '15])

Let  $d: X \times X \rightarrow [0,1]$  be a pseudo-metric and  $t_1, t_2 \in FX$ :

$$d^{\uparrow F}(t_1, t_2) = \sup\{d_e(ev(Ff(t_1)), ev(Ff(t_2))) \mid f: (X, d) \rightarrow ([0, 1], d_e) \text{ non-expansive}\}$$

where 
$$d_e(x, y) = |x - y|$$
 for  $x, y \in [0, 1]$ .

#### Given a pseudo-metric d:

- Take all non-expansive maps  $f:(X,d) \to ([0,1],d_e)$  (right adjoint).
- Take the predicate lifting for each such map.
- Generate a pseudo-metric from the predicate liftings obtained in this way (least pseudo-metric that makes all predicate liftings non-expansive) (left adjoint).

## Results (Functor Lifting)

- $d^{\uparrow F}$ ,  $d^{\downarrow F}$  are both pseudo-metrics (for the Wasserstein lifting we need some constraints on the evaluation function and weak pullback preservation)
- $d^{\uparrow F} \leq d^{\downarrow F}$ There are cases where  $d^{\uparrow F} < d^{\downarrow F}$ , i.e., the Kantorovich-Rubinstein duality does not necessarily hold (e.g. for  $FX = X \times X$ ).
- Non-expansive functions and isometries (distance-preserving functions) are preserved by lifting.
- The Wasserstein lifting preserves metrics (if the infimum is always a minimum).

Several standard metrics can be recovered by lifting. In each of these cases the Kantorovich-Rubinstein duality holds.

functor	evaluation fct.	resulting metric
$\mathcal{P}_{\mathit{fin}}$	$ev(R \subseteq [0,1]) = \max R$	Hausdorff
$\mathcal{D}$	$ev(p\colon [0,1]  o [0,1])$	
	$= \sum_{x \in [0,1]} x \cdot p(x)$	Kantorovich
X + Y	$ev(x \in [0,1]) = x$	distance on disjoint union
$X \times Y$	$ev(x,y) = \max\{x,y\}$	maximum of distances
$X \times Y$	ev(x,y) = x + y	sum of distances

Last three cases: bifunctor lifting or use of multiple evaluation maps

#### Is functor lifting compositional?

Assume that  $\overline{F}(X,d) = (FX,d^{\uparrow F})$  (Kantorovich) or  $\overline{F}(X,d) = (FX,d^{\downarrow F})$  (Wasserstein)

When does  $\overline{FG} = \overline{F} \overline{G}$  hold?

- Wasserstein:
  - $\overline{F}$   $\overline{G} \leq \overline{FG}$  always holds (if evaluation maps are composed)
  - Equality for so-called canonical liftings
- Kantorovich.
  - $\overline{FG} \leq \overline{F} \overline{G}$  always holds (if evaluation maps are composed)
  - Equality if F polynomial and chosen evaluation maps

Useful for defining up-to techniques that help to simplify (co)inductive proofs . . .

Let  $f: L \to L$  be a monotone function on a complete lattice. By Knaster-Tarski this function has a least fixpoint  $\mu f$  (that coincides with the least pre-fixpoint) and a greatest fixpoint  $\nu f$  (that coincides with the greatest post-fixpoint).

Idea: extend the usual proof rule for pre-fixpoints to a proof rule using an up-to function u.

$$\frac{f(d) \le d}{\mu f \le d} \qquad \frac{f(u(d)) \le d}{\mu f \le d}$$

Add an algebraic structure that interacts "nicely" with the coalgebraic structure:

#### Bialgebra

Consider two functors  $F, T: \mathbf{Set} \to \mathbf{Set}$  and a distributive law for a monad  $\zeta \colon TF \Rightarrow FT$ .

A bialgebra for  $\zeta$  consists of a T-algebra  $\beta: TX \to X$  and an *F*-coalgebra  $\gamma: X \to FX$  so that the diagram commutes.

$$TX \xrightarrow{\beta} X \xrightarrow{\gamma} FX$$

$$T\gamma \downarrow \qquad \uparrow F\beta$$

$$TFX \xrightarrow{\zeta_X} FTX$$

Such bialgebras can be obtained by determinizing coalgebras of the form  $Y \to FTY$ . In this case X = TY.

#### Coinduction Up-To [Bonchi, Petrişan, Pous, Rot, 2017]

Given a bialgebra  $\beta \colon TX \to X$ ,  $\gamma \colon X \to FX$  (with distr. law  $\zeta$ ):

- Lift the functors F, T to  $\overline{F}, \overline{T}$ : **PMet**  $\rightarrow$  **PMet**
- This gives us an up-to function u on the fibre above **PMet**<sub>X</sub>:

$$\mathsf{PMet}_X \xrightarrow{\overline{T}} \mathsf{PMet}_{TX} \xrightarrow{\Sigma_\beta} \mathsf{PMet}_X$$

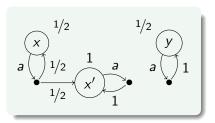
where  $\Sigma_{\beta}(d)(x_1, x_2) = \inf_{\beta(t_i)=x_i} d(t_1, t_2)$  (direct image). u is typically some form of metric congruence closure wrt. the operators of the algebra.

• Whenever  $\zeta$  can be extended to a natural transformation  $\zeta \colon \overline{T} \, \overline{F} \Rightarrow \overline{F} \, \overline{T}$  (i.e., the components of  $\zeta$  are non-expansive maps), the following proof rule holds:

$$\frac{f(u(d)) \le d}{\mu f \le d}$$

Up-to functions help to find witnesses (pre-fixed-points up-to), establishing upper bounds for least fixpoints.

Typically it is easier to show  $f(u(d)) \le d$  rather than  $f(d) \le d$ .



$$Q \rightarrow [0,1] \times \mathcal{D}(Q)^A$$

$\frac{tr_{x}(w)}{x}$	$ $ $\varepsilon$	а	aa	aaa	
Х	1/2	3/4	7/8	<sup>15</sup> / <sub>16</sub>	
У	1/2	1/2	1/2	1/2	ر

For a state  $x \in Q$  let  $tr_x : \Sigma^* \to [0,1]$  assign to each word  $w \in \Sigma^*$ the expected payoff for this word when read from x.

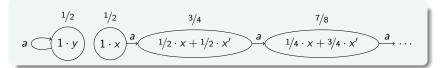
#### Directed behavioural distance between states:

$$d(x,y) = \sup_{w \in \Sigma^*} (tr_y(w) \ominus tr_x(w))$$

In this case: d(x, y) = 1/2.

This can be extended to probability distributions on states.

#### Probabilistic determinization:



Behavioral distance can be characterized as least fixpoint of f:

$$\begin{array}{cccc} f \colon [0,1]^{\mathcal{D}(Q) \times \mathcal{D}(Q)} & \to & [0,1]^{\mathcal{D}(Q) \times \mathcal{D}(Q)} \\ & f(d)(p,q) & = & \max\{|tr_p(\varepsilon) - tr_q(\varepsilon)|, \\ & & \max_{a \in \Sigma} \{\delta_a(p), \delta_a(q)\}\} \end{array}$$

 $tr_p(\varepsilon)$ : immediate payoff at p

Unfortunately, the state space is infinite . . .

Aim: show that  $d(x, y) \le 1/2$  in the example above.

Define finitary witness  $\bar{d}$ :

•  $\bar{d}(1 \cdot x, 1 \cdot y) = \frac{1}{2}, \ \bar{d}(1 \cdot x', 1 \cdot y) = \frac{1}{2}$  (1 in all other cases) and show that  $\bar{d}$  is a pre-fixpoint up-to.

$$f(u(\bar{d}))(1 \cdot x, 1 \cdot y) = \max\{|1/2 - 1/2|, u(\bar{d})(1/2 \cdot x + 1/2 \cdot x', y)\}$$

$$= u(\bar{d})(1/2 \cdot x + 1/2 \cdot x', y)$$

$$\leq 1/2 \cdot \bar{d}(1 \cdot x, 1 \cdot y) + 1/2 \cdot \bar{d}(1 \cdot x', 1 \cdot y)$$

$$= 1/2 \cdot 1/2 + 1/2 \cdot 1/2 = 1/2 = \bar{d}(1 \cdot x, 1 \cdot y)$$

The other case works similarly  $\Rightarrow \mu f = d \leq \bar{d}$ .

Use up-to approach to show that this reasoning is sound!

#### Instantiating the general approach:

- $\bullet$   $T=\mathcal{D}$
- $FX = [0,1] \times X^{\Sigma}$
- State space  $X = \mathcal{D}(Q)$  (probability distributions on Q)
- Coalgebra  $\gamma: X \to FX$ :  $\gamma \colon \mathcal{D}(Q) \to [0,1] \times \mathcal{D}(Q)^{\Sigma}$  (determinized probabilistic automaton)
- Algebra  $\beta \colon TX \to X$ :  $\beta \colon \mathcal{D}(\mathcal{D}(D)) \to \mathcal{D}(Q)$  (expectation/"flattening" nested probability distributions; multiplication of the monad)
- $\zeta_X : \mathcal{D}([0,1] \times X^{\Sigma}) \to [0,1] \times \mathcal{D}(X)^{\Sigma}$  ("probabilistic determinization")

**Lifting** the functors  $F, T: \mathbf{Set} \to \mathbf{Set}$  to [0,1]-**Graph**: Let  $d: X \times X \rightarrow [0,1]$ .

•  $FX = [0, 1] \times X^{\Sigma}$ :

$$\overline{F}(d)((a,x),(b,y)) = \max\{d_{\Sigma}(a,b),d(x,y)\}$$

(where  $d_{\Sigma}$  is a fixed metric on  $\Sigma$ ).

 $\bullet$   $T=\mathcal{D}$ :

 $\overline{T}(d)$  is the Kantorovich distance on probability distributions

- $f = \gamma^* \circ \overline{F}$ : behavioural distance function on the determinized probabilistic transition system ( $\overline{F}$ : Kantorovich lifting)
- $u = \Sigma_{\beta} \circ \overline{T}$ : contextual closure for barycentric algebras

$$u(d)(r_1 \cdot p_1 + r_2 \cdot p_2, r_1 \cdot q_1 + r_2 \cdot q_2) \leq r_1 \cdot d(p_1, q_1) + r_2 \cdot d(p_2, q_2)$$

See also work on quantitative algebraic reasoning [Mardare,Panangaden,Plotkin '16]

We proved some simple conditions ensuring that the distributive law can be lifted (for F polynomial and  $\overline{T}$  Kantorovich lifting) (plus additional results on Galois connections and compositionality): [D'Angelo,Gurke,Kirss,König,Najafi,Różowski,Wild, 2024]



Baldan, P., Bonchi, F., Kerstan, H., and König, B. (2018). Coalgebraic behavioral metrics.

Logical Methods in Computer Science, 14(3). Selected Papers of the 6th Conference on Algebra and Coalgebra in Computer Science (CALCO 2015).

Beohar, H., Gurke, S., König, B., Messing, K., Forster, J., Schröder, L., and Wild, P. (2024).

Expressive quantale-valued logics for coalgebras: an adjunction-based approach.

In *Proc. of STACS '24*, volume 289 of *LIPIcs*, pages 10:1–10:19. Schloss Dagstuhl – Leibniz Center for Informatics.



Bonchi, F., König, B., and Petrişan, D. (2023). Up-to techniques for behavioural metrics via fibrations.

Mathematical Structures in Computer Science, 33.

Special Issue 4–5: Differences and Metrics in Programs Semantics: Advances in Quantitative Relational Reasoning.

- Bonchi, F., Petrisan, D., Pous, D., and Rot, J. (2017). A general account of coinduction up-to.

  Acta Informatica, 54(2):127–190.
- D'Angelo, K., Gurke, S., Kirss, J. M., König, B., Najafi, M., Różowski, W., and Wild, P. (2024).

  Behavioural metrics: Compositionality of the Kantorovich lifting and an application to up-to techniques.

  In *Proc. of CONCUR '24*, volume 311 of *LIPIcs*, pages 20:1–20:19. Schloss Dagstuhl Leibniz Center for Informatics.
- de Alfaro, L., Faella, M., and Stoelinga, M. (2009). Linear and branching system metrics. IEEE Transactions on Software Engineering, 35(2):258–273.
- Forster, J., Schröder, L., Wild, P., Beohar, H., Gurke, S., and Messing, K. (2024).
  Graded semantics and graded logics for Eilenberg-Moore coalgebras.

In *Proc. of CMCS '24 (Coalgebraic Methods in Computer Science)*, pages 114–134. Springer. LNCS 14617.

Katsumata, S. and Sato, T. (2015).
 Codensity liftings of monads.
 In Proc. of CALCO '15, volume 35 of LIPIcs, pages 156–170.
 Schloss Dagstuhl – Leibniz Center for Informatics.

- Larsen, K. G. and Skou, A. (1989).
  Bisimulation through probabilistic testing (preliminary report).
  In *Proc. of POPL '89*, pages 344–352. ACM.
- Mardare, R., Panangaden, P., and Plotkin, G. (2016). Quantitative algebraic reasoning. In *Proc. of LICS '16*, pages 700–709. ACM.
- van Breugel, F. and Worrell, J. (2005). Approximating and computing behavioural distances in probabilistic transition systems.

Theoretical Computer Science, 360:373–385.



Villani, C. (2009).

Optimal Transport – Old and New, volume 338 of A Series of Comprehensive Studies in Mathematics.

Springer.