Labelled Markov Processes

Lecture 4: Metrics for Labelled Markov Processes

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Outline

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Process Equivalence is Fundamental

- Markov chains:
- Lumpability
- Labelled Markov processes: Bisimulation
- Markov decision processes: Bisimulation
- Labelled Concurrent Markov Chains with τ transitions: Weak Bisimulation

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- In the context of probability is exact equivalence reasonable?
- We say “no”. A small change in the probability distributions may result in bisimilar processes no longer being bisimilar though they may be very “close” in behaviour.
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Bisimulation

- Let R be an equivalence relation. R is a bisimulation if: $s\ R\ t$ if $(\forall\ a)$:

$$(s \xrightarrow{a} P) \Rightarrow [t \xrightarrow{a} Q, P =_R Q]$$

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Properties of Bisimulation

- Establishing equality of states: Coinduction. Establish a bisimulation R that relates states s, t.
- Distinguishing states: Simple logic is complete for bisimulation.

$$\phi ::= \mathtt{true} \mid \phi_1 \wedge \phi_2 \mid \langle a \rangle_{>q} \phi$$

- Bisimulation is sound for much richer logic pCTL*.
- Bisimulation is a congruence for usual process operators.

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A metric-based approximate viewpoint

- Move from equality between processes to distances between processes (Jou and Smolka 1990).
- Formalize distance as a metric:

$$d(s,s) = 0, d(s,t) = d(t,s), d(s,u) \leq d(s,t) + d(t,u).$$

  Quantitative analogue of an equivalence relation.
- Quantitative measurement of the distinction between processes.

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Summary of results

- Establishing closeness of states: Coinduction
- Distinguishing states: Real-valued modal logics
- Equational and logical views coincide: Metrics yield same distances as real-valued modal logics
- Compositional reasoning by *Non-Expansivity*. Process-combinators take nearby processes to nearby processes.

$$\frac{d(s_1, t_1) < \epsilon_1, \qquad d(s_2, t_2) < \epsilon_2}{d(s_1 \mid\mid s_2, t_1 \mid\mid t_2) < \epsilon_1 + \epsilon_2}$$

- Results work for Markov chains, Labelled Markov processes, Markov decision processes and Labelled Concurrent Markov chains with τ-transitions.

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Criteria on Metrics

- Soundness:

$$d(s,t) = 0 \Leftrightarrow s, t \text{ are bisimilar}$$

- Stability of distance under temporal evolution:“Nearby states stay close *forever*.”
- Metrics should be computable (efficiently?).

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where $P =_R Q$ if

$$(\forall R - \text{closed } E)\ P(E) = Q(E)$$

A putative definition of a metric-bisimulation

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A detour: Kantorovich metric

- Metrics on probability measures on metric spaces.
- $\mathcal{M}$: 1-bounded pseudometrics on states.
- $$d(\mu, \nu) = \sup_f \left| \int f d\mu - \int f d\nu \right|, f \text{ 1-Lipschitz}$$
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An LP version for Finite-State Spaces

When state space is finite: Let P, Q be probability distributions. Then:

$$m(P, Q) = \max \sum_i (P(s_i) - Q(s_i))a_i$$

subject to:

$$\forall i. 0 \leq a_i \leq 1$$
$$\forall i, j.\ a_i - a_j \leq m(s_i, s_j).$$

The Dual Form

- Dual form from Worrell and van Breugel:
- $$\min \sum_{i,j} l_{ij} m(s_i, s_j) + \sum_i x_i + \sum_j y_j$$

  subject to:

  $$\begin{array}{l} \forall i. \sum_j l_{ij} + x_i = P(s_i) \\ \forall j. \sum_i l_{ij} + y_j = Q(s_j) \\ \forall i, j.\ l_{ij}, x_i, y_j \geq 0. \end{array}$$
- We prove many equations by using the primal form to show one direction and the dual to show the other.

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Example 1

- $m(P, P) = 0$.
- In dual, match each state with itself, $l_{ij} = \delta_{ij} P(s_i), x_i = y_j = 0$. So:

$$\sum_{i,j} l_{ij} m(s_i, s_j) + \sum_i x_i + \sum_j y_j$$

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Example 2

- Let $m(s,t) = r < 1$. Let $\delta_s(\delta_t)$ be the probability measure concentrated at $s(t)$. Then,

$$m(\delta_s, \delta_t) = r$$

- Upper bound from dual: Choose $l_{st} = 1$ all other $l_{ij} = 0$. Then

$$\sum_{ij} l_{ij} m(s_i, s_j) = m(s,t) = r.$$

- Lower bound from primal: Choose $a_s = 0, a_t = r$, all others to match the constraints. Then

$$\sum_i (\delta_t(s_i) - \delta_s(s_i))a_i = r.$$

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The Importance of Example 2

We can *isometrically* embed the original space in the metric space of distributions.

Example 3 - I

- Let $P(s) = r, P(t) = 0$ if $s \neq t$. Let $Q(s) = r', Q(t) = 0$ if $s \neq t$.
- Then $m(P, Q) = |r - r'|$.
- Assume that $r \geq r'$.
  Lower bound from primal: yielded by $\forall i. a_i = 1$,

$$\sum_i (P(s_i) - Q(s_i))a_i = P(s) - Q(s) = r - r'.$$

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Example 3 - II

Upper bound from dual: $l_{ss} = r'$ and $x_s = r - r'$, all others 0

$$\sum_{i,j} l_{ij} m(s_i, s_j) + \sum_i x_i + \sum_j y_j = x_s = r - r'.$$

and the constraints are satisfied:

$$\sum_j l_{sj} + x_s = l_{ss} + x_s = r$$

$$\sum_i l_{is} + y_s = l_{ss} = r'.$$

Return from Detour

Summary of detour: Given a metric on states in a metric space, can lift to a metric on probability distributions on states.

Metric “Bisimulation”

- m is a metric-bisimulation if: $m(s,t) < \epsilon \Rightarrow$:

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- The required canonical metric on processes is the least such: ie. the distances are the least possible.
- Thm: *Canonical least metric exists*. Usual fixed-point theory arguments.

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Metrics: some details

- $\mathcal{M}$: 1-bounded pseudometrics on states with ordering

$$m_1 \preceq m_2 \text{ if } (\forall s,t)\ [m_1(s,t) \geq m_2(s,t)]$$

- $(\mathcal{M}, \preceq)$ is a complete lattice.
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$$\begin{aligned} \bot(s,t) &= \begin{cases} 0 \text{ if } s = t \\ 1 \text{ otherwise} \end{cases} \\ \top(s,t) &= 0, (\forall s,t) \\ (\sqcap\{m_i\}(s,t) &= \sup_i m_i(s,t) \end{aligned}$$

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Maximum fixed point definition

- Let $m \in \mathcal{M}$. $F(m)(s,t) < \epsilon$ if:

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- $F(m)(s,t)$ can be given by an explicit expression.
- F is monotone on $\mathcal{M}$, and metric-bisimulation is the greatest fixed point of F.
- The closure ordinal of F is ω.

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A Key Tool: Splitting

Let P and Q be probability distributions on a set of states. Let P_1 and P_2 be such that: $P = P_1 + P_2$. Then, there exist Q_1, Q_2, such that $Q_1 + Q_2 = Q$ and

$$m(P, Q) = m(P_1, Q_1) + m(P_2, Q_2).$$

The proof uses the duality theory of LP.

What about Continuous-State Systems?

- Develop a real-valued “modal logic” based on the analogy:

Program Logic	Probabilistic Logic
State s	Distribution μ
Formula ϕ	Random Variable f
Satisfaction $s \models \phi$	$\int f \, \mathrm{d}\mu$

- Define a metric based on how closely the random variables agree.
- We did this *before* the LP based techniques became available.

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Real-valued Modal Logic

- $$f ::= \mathbf{1} \mid \max(f, f) \mid h \circ f \mid \langle a \rangle . f$$

$\mathbf{1}(s)$	$=$	1	True
$\max(f_1, f_2)(s)$	$=$	$\max(f_1(s), f_2(s))$	Conjunction
$h \circ f(s)$	$=$	$h(f(s))$	Lipschitz
$\langle a \rangle . f(s)$	$=$	$\gamma \int_{s' \in S} f(s') \tau_a(s, ds')$	a-transition

  where h 1-Lipschitz : $[0, 1] \to [0, 1]$ and $\gamma \in (0, 1]$.
- $d(s, t) = \sup_f |f(s) - f(t)|$
- Thm: d coincides with the canonical metric-bisimulation.

Real-valued Modal Logic

- $$f ::= \mathbf{1} \mid \max(f, f) \mid h \circ f \mid \langle a \rangle .f$$

- $$\begin{array}{lcll} \mathbf{1}(s) & = & 1 & \text{True} \\ \max(f_1, f_2)(s) & = & \max(f_1(s), f_2(s)) & \text{Conjunction} \\ h \circ f(s) & = & h(f(s)) & \text{Lipschitz} \\ \langle a \rangle .f(s) & = & \gamma \int_{s' \in S} f(s') \tau_a(s, ds') & a\text{-transition} \end{array}$$

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Finitary syntax for Real-valued modal logic

$\mathbf{1}(s)$	$=$	1	True
$\max(f_1, f_2)(s)$	$=$	$\max(f_1(s), f_2(s))$	Conjunction
$(1 - f)(s)$	$=$	$1 - f(s)$	Negation
$\lfloor f_q(s) \rfloor$	$=$	$\begin{cases} q \ , & f(s) \geq q \\ f(s) \ , & f(s) < q \end{cases}$	Cutoffs
$\langle a \rangle . f(s)$	$=$	$\gamma \int_{s' \in S} f(s') \tau_a(s, \mathrm{d}s')$	a-transition

q is a rational.

The role of γ

- γ discounts the value of future steps.
- $\gamma < 1$ and $\gamma = 1$ yield very different topologies
- The approximants defined last week converge in the metric $\gamma < 1$.
- The $\gamma < 1$ metric yields the Lawson topology.
- For $\gamma < 1$ there is an LP-based strongly-polynomial (in the number of constraints, and the number of bits of precision required) algorithm to compute the metric.
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Conclusions

- For a CSP-like process algebra (without hiding) the process combinators are all contractive.
- We can show that if one perturbs the probabilities slightly the resulting process is close to the unperturbed one.
- We have an asymptotic version of the metric.
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