Higher-Order Probabilistic Programming

A Tuotorial at POPL 2019

Part III

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(Based on joint work with Flavien Breuvart, Raphaëlle Crubillé, Charles Grellois, Davide Sangiorgi,...)



POPL 2019, Lisbon, January 14th

Equivalence and Distance Checking

▶ How could we check two higher-order probabilistic programs to be (context) equivalent?

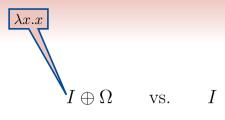
Equivalence and Distance Checking

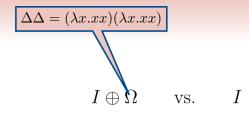
- ▶ How could we check two higher-order probabilistic programs to be (context) equivalent?
- ▶ How about their distance?

Equivalence and Distance Checking

- ▶ How could we check two higher-order probabilistic programs to be (context) equivalent?
- ▶ How about their distance?
- Contextual equivalence and contextual distance are good answers, definitionally.
 - They are the coarsest compatible and adequate relation and metric between programs.
 - ► There is however an explicit quantification over all contexts, which make argument inherently complicated.

 $I \oplus \Omega$ vs. I





Not Context Equivalent: $C = [\cdot]$.

Context Distance? Consider $C_n = (\lambda x. \ \underline{x \dots x})[\cdot]$.

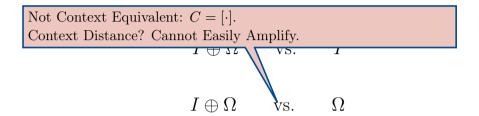
n times

 $I \oplus \Omega$

Б.

 $I \oplus \Omega$ vs. I

 $I \oplus \Omega$ vs. Ω



$$I\oplus\Omega$$
 vs. I $I\oplus\Omega$ vs. Ω

 $(\lambda x.I) \oplus (\lambda x.\Omega)$ vs. $\lambda x.I \oplus \Omega$

$$I\oplus\Omega \qquad \text{vs.} \qquad I$$
 Not Context Equivalent in CBV: $C=(\lambda x.x(xI))[\cdot]$ Apparently Context Equivalent in CBN.
$$I\oplus \mathfrak{sl} \qquad \text{vs.} \qquad \mathfrak{sl}$$

$$(\lambda x.I)\oplus(\lambda x.\Omega) \qquad \text{vs.} \qquad \lambda x.I\oplus\Omega$$

$$I \oplus \Omega$$
 vs. I $I \oplus \Omega$ vs. Ω $(\lambda x.I) \oplus (\lambda x.\Omega)$ vs. $\lambda x.I \oplus \Omega$ Y_1 vs. Y_2

$$I \oplus \Omega$$
 vs. I

$$Y_1M \to^* M(Y_2M) \oplus M(Y_3M)$$
 $Y_2M \to^* M(Y_1M) \oplus M(Y_3M)$
 $Y_3M \to^* M(Y_1M) \oplus M(Y_2M)$
 $Y_1 \qquad \text{VS.} \qquad Y_2$

Probabilistic Bisimulation in the Abstract [LS1992]

- ▶ Labelled Markov Chain (LMC): a triple $\mathcal{M} = (\mathcal{S}, \mathcal{L}, \mathcal{P})$, where
 - \triangleright S is a countable set of *states*;
 - \triangleright \mathcal{L} is a set of *labels*;
 - ▶ \mathcal{P} is a transition probability matrix, i.e., a function $\mathcal{P}: \mathcal{S} \times \mathcal{L} \times \mathcal{S} \to \mathbb{R}$ such that for every state t and for every label ℓ , $\mathcal{P}(t,\ell,\mathcal{S}) = \sum_{s \in \mathcal{S}} \mathcal{P}(t,\ell,s) \leq 1$;
- ▶ **Bisimulation**: equivalence relation \mathcal{R} on \mathcal{S} such that whenever $t \mathcal{R} s$, it holds that $\mathcal{P}(t,\ell,E) = \mathcal{P}(s,\ell,E)$ for every equivalence class E of \mathcal{S} modulo \mathcal{R} .
- ▶ Variation: **Simulation**, which is required to be a preorder.
- ▶ Bisimilarity and Similarity can always be formed.

Proposition

$$\sim = \preceq \cap \preceq^{op}$$
.

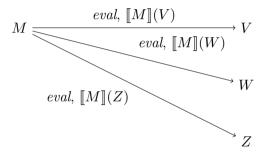
Terms

Terms Values

Terms Values

M

Terms Values



:

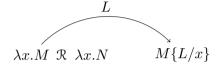
 $\overline{\text{Terms}}$

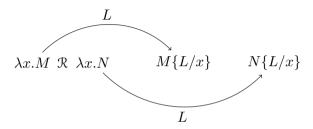
 $\lambda x.N$

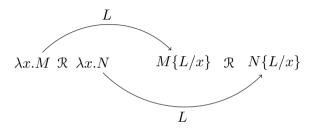
Values

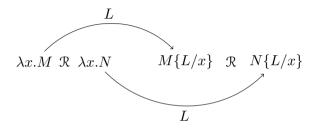
Terms		Values
$N\{W/x\} \longleftarrow$	W,1	$ \lambda x.N$

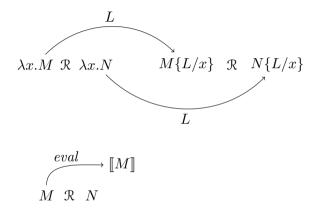
 $\lambda x.M \mathcal{R} \lambda x.N$

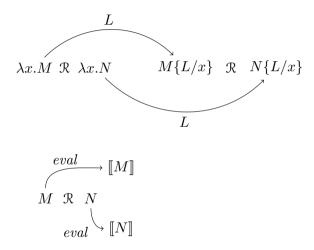


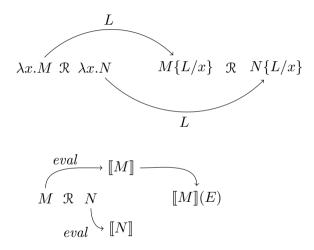


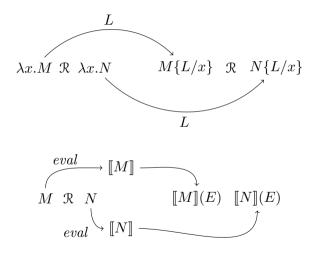


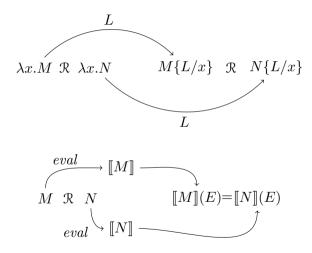












Applicative Bisimilarity vs. Context Equivalence

- **Bisimilarity**: the union \sim of all bisimulation relations.
- ▶ Is it that \sim is included in \equiv ? How to prove it?
- ▶ Natural strategy: is \sim a congruence?
 - ▶ If this is the case:

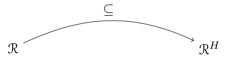
$$M \sim N \implies C[M] \sim C[N] \implies \sum \llbracket C[M] \rrbracket = \sum \llbracket C[N] \rrbracket$$

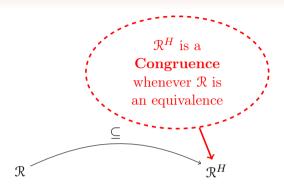
 $\implies M \equiv N.$

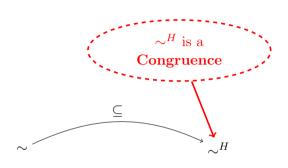
- ▶ This is a necessary sanity check anyway.
- ▶ The naïve proof by induction **fails**, due to application: from $M \sim N$, one cannot directly conclude that $LM \sim LN$.

R

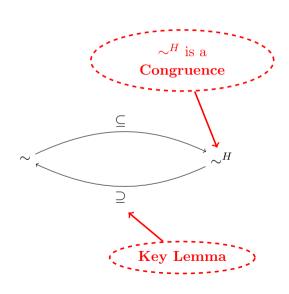
 \mathfrak{R}^H







Howe's Technique



Our Neighborhood

 \blacktriangleright Λ , where we observe **convergence**

	\sim \subseteq \equiv	\equiv \subseteq \sim
CBN	√	✓
CBV	✓	✓

[Abramsky1990, Howe1993]

▶ Λ_{\oplus} with nondeterministic semantics, where we observe **convergence**, in its **may** or **must** flavors.

	= =	~ □
CBN	√	×
CBV	√	×

[Ong1993, Lassen1998]

	\sim \subseteq \equiv	\equiv \subseteq \sim
CBN	✓	×
CBV	√	√

	$\equiv \\ \subseteq \\ \sim$	~ ∪
CBN	✓	×
CBV	✓	✓

- ▶ Counterexample for CBN: $(\lambda x.I) \oplus (\lambda x.\Omega) \nsim \lambda x.I \oplus \Omega$
- ▶ Where these discrepancies come from?

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CBN	✓	×
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- ▶ Where these discrepancies come from?
- ► From **testing!**
- ▶ Bisimulation can be characterized by testing equivalence as follows:

Calculus	Testing	
Λ	$T ::= \omega \mid a \cdot T$	
probabilistic Λ_{\oplus}	$T ::= \omega \mid a \cdot T \mid \langle T, T \rangle$	
nondeterministic Λ_{\oplus}	$T ::= \omega \mid a \cdot T \mid \wedge_{i \in I} T_i \mid \dots$	

	$\lesssim \subseteq \leq$	\leq \subseteq \lesssim
CBN	✓	×
CBV	√	×

▶ Λ_{\oplus} with probabilistic semantics.

	$\lesssim \subseteq \leq$	\leq \subseteq \lesssim
CBN	✓	×
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▶ Probabilistic simulation can be characterized by testing as follows:

$$T ::= \omega \mid a \cdot T \mid \langle T, T \rangle \mid T \vee T$$

▶ Λ_{\oplus} with probabilistic semantics.

	$\preceq \subseteq \leq$	\leq \subseteq \lesssim
CBN	✓	×
CBV	√	×

▶ Probabilistic simulation can be characterized by testing as follows:

$$T ::= \omega \mid a \cdot T \mid \langle T, T \rangle \mid T \vee T$$

▶ Full abstraction can be recovered if endowing Λ_{\oplus} with parallel disjunction [CDLSV2015].

	$\lesssim \subseteq \leq$	\leq \subseteq \lesssim
CBN	✓	×
CBV	✓	✓

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$$\frac{x, \Gamma \vdash M}{\Gamma, x \vdash x} \quad \frac{x, \Gamma \vdash M}{\Gamma \vdash \lambda x. M} \quad \frac{\Gamma \vdash M}{\Gamma, \Delta \vdash MN} \quad \frac{\Gamma \vdash M}{\Gamma \vdash M \oplus N} \quad \frac{\Gamma \vdash M}{\Gamma \vdash M \oplus N}$$

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- ▶ Soundness and Completeness Results:

$\delta^b \leq \delta^c$	$\delta^c \le \delta^b$	$\delta^t \leq \delta^c$	$\delta^c \leq \delta^t$
✓	×	✓	✓

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✓	×	✓	✓

▶ Example: $\delta^t(I, I \oplus \Omega) = \delta^t(I \oplus \Omega, \Omega) = \frac{1}{2}$.

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 - ▶ **Terms**: any preterm M such that $\Gamma \vdash M$.
 - ▶ States: sequences of terms, rather than terms.
 - ▶ Actions not only model parameter passing, but also *copying* of terms.

Context $\frac{|\Gamma, x \vdash x|}{|\Gamma, x \vdash x|} \frac{|x, \Gamma \vdash M|}{|\Gamma \vdash \lambda x. M|} \frac{|x, \Gamma \vdash M|}{|\Gamma \vdash \lambda x. M|}$ $\frac{|\Gamma \vdash M|}{|\Gamma \vdash |M|} \frac{|\Gamma, !\Theta \vdash M|}{|\Gamma, \Delta, \Theta \vdash MN|} \frac{|\Gamma \vdash M|}{|\Gamma \vdash M \oplus N|}$

► A Tuple LMC.

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- ▶ None of the abstract notions of distance δ gives us that $\delta(I, I \oplus \Omega) = 1$.
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\checkmark	✓	

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δ	$t \leq \delta^c$	$\delta^c \leq \delta^t$	
✓		✓	

▶ Examples: $\delta^t(!(I \oplus \Omega), !\Omega) = \frac{1}{2}$ $\delta^t(!(I \oplus \Omega), !I) = 1$.

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$\delta^t \le \delta^c$	$\delta^c \leq \delta^t$	
✓	✓	

- **Examples:** $\delta^t(!(I \oplus \Omega), !\Omega) = \frac{1}{2}$ $\delta^t(!(I \oplus \Omega), !I) = 1$.
- ▶ **Trivialisation** does not hold in general, but becomes true in *strongly* normalising fragments or in presence of parellel disjuction.

- ▶ Probabilistic Powerdomains [JonesPlotkin1991, JungTix1998].
 - ▶ Probabilistic effects are interpreted in *monadic* style [Moggi1989].
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 - ► Can adequately model continuous distributions and conditioning.
- ▶ Game and GoI Models [DanosHarmer2002, DLFVY2017].
 - ▶ Higher-order programs are interpreted as strategies or automata.
 - ▶ Game models are fully abstract, in presence of states.

Thank You!

Questions?