

# Structural Operational Semantics for continuous state probabilistic processes\*

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# Structural Operational Semantics for CCS

Syntax:  $P ::= \text{nil} \mid a.P \mid \bar{a}.P \mid \tau.P \mid P + P \mid P \parallel P \quad (a \in A)$

$$\Sigma X = \overbrace{1}^{\text{nil}} + \overbrace{A \times X}^{a.x} + \overbrace{A \times X}^{\bar{a}.x} + \overbrace{X}^{\tau.x} + \overbrace{X \times X}^{x+x} + \overbrace{X \times X}^{x \parallel x}$$

$$\frac{}{\alpha.x \xrightarrow{\alpha} x} \quad \frac{x \xrightarrow{\alpha} x'}{x + y \xrightarrow{\alpha} x'} \quad \frac{y \xrightarrow{\alpha} y'}{x + y \xrightarrow{\alpha} y'}$$

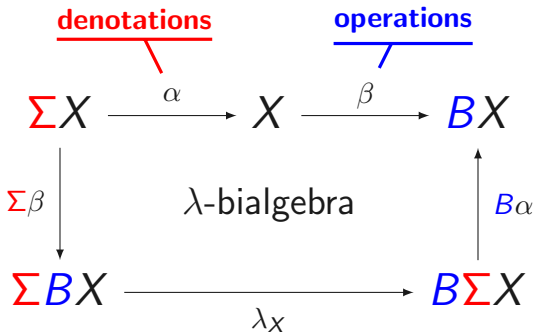
$$\frac{x \xrightarrow{\alpha} x'}{x \parallel y \xrightarrow{\alpha} x' \parallel y} \quad \frac{y \xrightarrow{\alpha} y'}{x \parallel y \xrightarrow{\alpha} x \parallel y'}$$

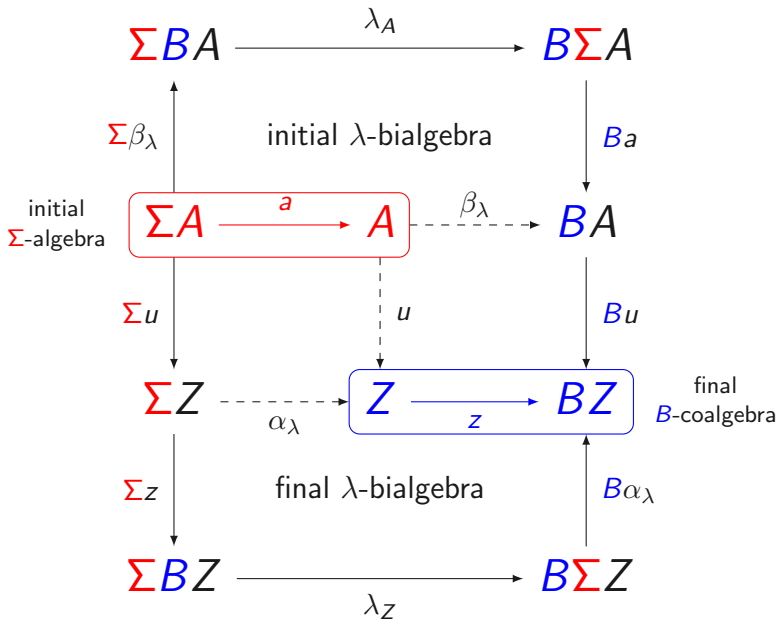
$$\frac{x \xrightarrow{a} x' \quad y \xrightarrow{\bar{a}} y'}{x \parallel y \xrightarrow{\tau} x' \parallel y'} \quad \frac{x \xrightarrow{\bar{a}} x' \quad y \xrightarrow{a} y'}{x \parallel y \xrightarrow{\tau} x' \parallel y'}$$

This corresponds to:  $\lambda: \Sigma(\text{Id} \times (\mathcal{P}_{\text{fin}})^L) \Rightarrow (\mathcal{P}_{\text{fin}} T_{\Sigma})^L$

# Abstract Structural Operational Semantics

(distributing **syntax** over **behaviours**:  $\lambda: \Sigma B \Rightarrow B\Sigma$ )





# Benefits of the bialgebraic framework

[Turi-Plotkin'97]

- + denotational model on the final  $B$ -coalgebra (by co-induction)
- + operational model on the initial  $\Sigma$ -algebra (by induction)
  
- + universal semantics (full-abstraction)
  - initial algebra semantics = final coalgebra semantics
- +  $B$ -behavioural equivalence is a  $\Sigma$ -congruence
- +  $B$ -bisimilarity is a  $\Sigma$ -congruence (if  $B$  pres. weak pullbacks)

# Congruential Rule Formats [Turi-Plotkin'97]

Distributive laws can be specified as sets of derivation rules

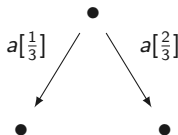
$$\left\{ \frac{\left\{ \left\{ x_i \xrightarrow{a} y_{ij}^a \right\}_{1 \leq j \leq m_i^a} \right\}_{1 \leq i \leq n, a \in A_i} \quad \left\{ x_i \xrightarrow{b} \right\}_{1 \leq i \leq n, b \in B_i}}{f(x_1, \dots, x_n) \xrightarrow{c} t} \right\}_{\text{image finite}} \quad (\text{GSOS})$$

corresponds to...

$$\lambda: \Sigma(\text{Id} \times (\mathcal{P}_{\text{fin}})^L) \Rightarrow (\mathcal{P}_{\text{fin}} T_\Sigma)^L$$

# Discrete state sub-Probabilistic Systems

... hence labelled sub-probabilistic Markov chains



$$X \rightarrow (\mathcal{D}_{\text{fin}} X)^L \quad \text{in } \mathbf{Set}$$

where

$\mathcal{D}_{\text{fin}} : \mathbf{Set} \rightarrow \mathbf{Set}$  (sub-probability distribution functor)

$$\mathcal{D}_{\text{fin}} X = \{ \varphi : X \rightarrow [0, 1] \mid \sum_{x \in X} \varphi(x) \leq 1, |\text{supp}(\varphi)| < \infty \}$$

# Rule Formats for Probabilistic Systems

[Bartels'04]

$$\left\{ \begin{array}{l} x_i \xrightarrow{a} \quad a \in A_i, 1 \leq i \leq n \\ x_i \not\xrightarrow{b} \quad b \in B_i, 1 \leq i \leq n \\ x_{a_j} \xrightarrow{I_j[p_j]} y_j \quad 1 \leq j \leq J \\ \hline f(x_1, \dots, x_n) \xrightarrow{c[w \cdot p_1 \dots p_J]} t \end{array} \right\} \text{image finite}$$

corresponds to...

$$\lambda: \Sigma (Id \times (\mathcal{D}_{\text{fin}})^L) \Rightarrow (\mathcal{D}_{\text{fin}} T_\Sigma)^L$$

where

$\mathcal{D}_{\text{fin}}: \mathbf{Set} \rightarrow \mathbf{Set}$  (sub-probability distribution functor)

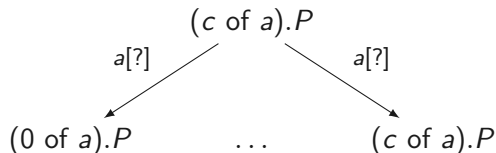
$$\mathcal{D}_{\text{fin}} X = \{ \varphi: X \rightarrow [0, 1] \mid \sum_{x \in X} \varphi(x) \leq 1, |\text{supp}(\varphi)| < \infty \}$$



Let us extend CCS with a quantitative operator

$$P ::= \text{nil} \mid (c \text{ of } \alpha).P \mid P + P \mid P \parallel P \quad (c \in \mathbb{R}_{\geq 0})$$

$$\alpha ::= a \mid \bar{a} \mid \tau \quad (a \in A)$$

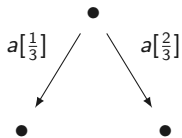


ideally we want that the outcomes are uniformly distributed. . .

$$U((c \text{ of } a).P)(\{(i \text{ of } a).P \mid i \in [a, b]\}) = \int_a^b \frac{1}{c} dx \quad (0 \leq a \leq b \leq c)$$

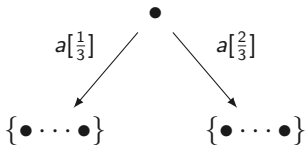
## Discrete state

(labelled Markov chains)



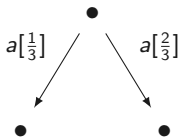
## Continuous state

(labelled Markov processes)



## Discrete state

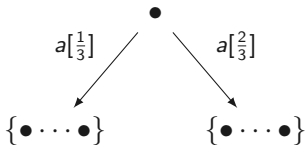
(labelled Markov chains)



$X \rightarrow (\mathcal{D}_{\text{fin}} X)^L$  in **Set**

## Continuous state

(labelled Markov processes)



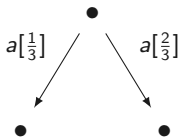
$\mathcal{D}_{\text{fin}} : \mathbf{Set} \rightarrow \mathbf{Set}$

(sub-probability distribution functor)

$$\mathcal{D}_{\text{fin}} X = \{ \varphi : X \rightarrow [0, 1] \mid \sum_{x \in X} \varphi(x) \leq 1, |\text{supp}(\varphi)| < \infty \}$$

## Discrete state

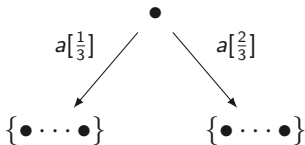
(labelled Markov chains)



$X \rightarrow (\mathcal{D}_{\text{fin}} X)^L$  in **Set**

## Continuous state

(labelled Markov processes)



$X \rightarrow (\Delta X)^L$  in **Meas**

$\mathcal{D}_{\text{fin}}: \mathbf{Set} \rightarrow \mathbf{Set}$  (sub-probability distribution functor)

$$\mathcal{D}_{\text{fin}} X = \{ \varphi: X \rightarrow [0, 1] \mid \sum_{x \in X} \varphi(x) \leq 1, |\text{supp}(\varphi)| < \infty \}$$

$\Delta: \mathbf{Meas} \rightarrow \mathbf{Meas}$  (Giry functor)

$$\Delta X = \{ \mu: \Sigma_X \rightarrow [0, 1] \mid \mu \text{ sub-probability measure} \}$$

**Aim:** Congruential Rule Formats  
for Probabilistic Processes  
with Continuous State Spaces


... hence, inducing distributive laws of type

$$\lambda: \Sigma(Id \times \Delta^L) \Rightarrow (\Delta T_\Sigma)^L$$

# The shape of transitions


The behaviour functor suggests the shape of transitions. . .

**Discrete state**

$$t \xrightarrow{a[\rho]} t'$$


$\Sigma$ -term

**Continuous state**

$$t \xrightarrow{a} \mu$$


measure  
on  $\Sigma$ -terms

## The Measurable Space of Stochastic Processes

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 The Microsoft Research-University of Trento  
 Centre for Computational and Systems Biology  
 Trento, Italy  
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(Null).

$$\overline{0 \rightarrow \bar{\omega}}$$

(Guard).

$$\overline{\varepsilon.P \rightarrow [\varepsilon_P]}$$

(Sum).

$$\frac{P \rightarrow \mu' \quad Q \rightarrow \mu''}{P + Q \rightarrow \mu' \oplus \mu''}$$

(Par).

$$\frac{P \rightarrow \mu' \quad Q \rightarrow \mu''}{P|Q \rightarrow \mu' \ P \otimes_Q \ \mu''}$$

Table I  
 STRUCTURAL OPERATIONAL SEMANTICS

## The Measurable Space of Stochastic Processes

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Table I  
 STRUCTURAL OPERATIONAL SEMANTICS

rather ac  
 (no general

# Measure terms

We adopt a new syntax to handle measures syntactically

$\Sigma$ : **Meas**  $\rightarrow$  **Meas** (process syntax)

$M$ : **Meas**  $\rightarrow$  **Meas** (measure syntax)

$$t \xrightarrow{a} \mu$$



it's a  $M$ -term!

## Measure GSOS rule format

$$\frac{\left\{ X_i \xrightarrow{a_{ij}} \mu_{ij} \right\}_{\substack{1 \leq j \leq m_i \\ 1 \leq i \leq n, a_{ij} \in A_i}} \quad \left\{ X_i \not\xrightarrow{b} \right\}_{\substack{b \in B_i \\ 1 \leq i \leq n}}}{f(x_1, \dots, x_n) \xrightarrow{c} \mu} \quad (\text{MG SOS})$$

where

- +  $f \in \Sigma$  with  $ar(f) = n$ ;
- +  $\{x_1, \dots, x_n\}$  and  $\{\mu_{ij} \mid 1 \leq i \leq n, 1 \leq j \leq m_i\}$  are pairwise distinct process and measure variables;
- +  $A_i \cap B_i = \emptyset$  are disjoint subsets of labels in  $L$ , and  $c \in L$ ;
- +  $\mu$  is a  $M$ -term with variables in  $\{x_1, \dots, x_n\}$  and  $\{\mu_{ij} \mid 1 \leq i \leq n, 1 \leq j \leq m_i\}$ .

# Measure GSOS specification systems

An MGSOS specification system consists of

## Set of MGSOS rules:

$$\mathcal{R} = \left\{ \frac{\left\{ \begin{array}{l} \{x_i \xrightarrow{a_{ij}} \mu_{ij}\}_{1 \leq j \leq m_i} \\ \{x_i \not\xrightarrow{b_i}\}_{1 \leq i \leq n, b_i \in B_i} \end{array} \right.}{f(x_1, \dots, x_n) \xrightarrow{c} \mu} \right\} \text{ image finite}$$

## Measure terms interpretation:

$$\langle \cdot \rangle : T_M \Delta \Rightarrow \Delta T_\Sigma$$

# From MGSOS to labelled Markov processes

We can obtain a  $\Delta^L$ -coalgebra on the set of closed  $\Sigma$ -terms

$$\gamma: T_{\Sigma}0 \rightarrow \Delta^L T_{\Sigma}0$$

as

$$\gamma(\mathbf{t})(\alpha) = \bigoplus_{T_{\Sigma}0} (\{ \langle \mu \rangle_{T_{\Sigma}0} \mid \mathbf{t} \xrightarrow{\alpha} \mu \})$$

where, for a finite set of  $U = \{\mu_1, \dots, \mu_n\}$  of sub-probability measures over  $X$ ,

$$\bigoplus_X (\{\mu_1, \dots, \mu_n\})(E) = \frac{\mu_1(E) + \dots + \mu_n(E)}{\mu_1(X) + \dots + \mu_n(X)}$$

(weighted sum of sub-probability measures)

# Example: Quantitative CCS

Measure terms syntax:

$$\mu ::= U_c^\alpha[P] \mid D[P] \mid \mu|\mu \mid \mu \blacktriangledown_{c,c'} \mu \quad (c, c' \in \mathbb{R}_{\geq 0})$$

Measure GSOS Rules\*:

$$\begin{array}{c} \frac{}{(c \text{ of } \alpha).x \xrightarrow{\alpha,c} U_c^\alpha[x]} \\ \frac{x \xrightarrow{\alpha,c} \mu}{x + x' \xrightarrow{\alpha,c} \mu} \\ \frac{x \xrightarrow{\alpha,c} \mu \quad x' \xrightarrow{\alpha,c'} \mu'}{x \parallel x' \xrightarrow{\alpha,c+c'} \mu|\mu'} \end{array} \qquad \begin{array}{c} \frac{}{(0 \text{ of } \alpha).x \xrightarrow{\tau} D[x]} \\ \frac{x \xrightarrow{\alpha,c} \mu}{x \parallel x' \xrightarrow{\alpha,c} \mu|D[x']} \\ \frac{x \xrightarrow{a,c} \mu \quad x' \xrightarrow{\bar{a},c'} \mu'}{x \parallel x' \xrightarrow{\tau} \mu \blacktriangledown_{c,c'} \mu'} \end{array}$$

(\*) dual rules for + and || are omitted

# Example: Quantitative CCS

Measure term interpretation:

$$\langle \cdot \rangle_X : T_M \Delta X \Rightarrow \Delta T_\Sigma X$$

$$\langle U_c^\alpha[x] \rangle_X(E) = \int_{E'} \frac{1}{c} dy \quad \text{where } E' = [0, c] \cap (\lambda \epsilon. (\epsilon \text{ of } \alpha).x)^{-1}(E)$$

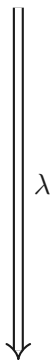
$$\langle D[x] \rangle_X(E) = \begin{cases} 1 & \text{if } x \in E \\ 0 & \text{otherwise} \end{cases}$$

$$\langle \mu | \mu' \rangle_X(E) = (\langle \mu \rangle_X \otimes \langle \mu' \rangle_X) \circ (\lambda(x, x'). x \parallel x')^{-1}(E)$$

$$\langle \mu \blacktriangleright_{c,c'} \mu' \rangle_X(E) = \begin{cases} 1 & \text{if } c \cdot \langle \mu \rangle_X(A_1) = c' \cdot \langle \mu' \rangle_X(A_2), \\ & \text{for } A_i = \pi_i((\lambda(x, x'). x \parallel x')^{-1}(E)) \\ 0 & \text{otherwise} \end{cases}$$

# From MGSOS to distributive laws

$$\Sigma(Id \times \Delta^L)$$



$$(\Delta T_{\Sigma})^L$$

how do we get the distributive law  $\lambda$   
out of an MGSOS specification systems?



$$\Sigma(Id \times \Delta^L)$$

$$\Downarrow \llbracket \mathcal{R} \rrbracket$$

$$(\mathcal{P}_{\text{fin}} T_M \Delta)^L$$

1. define the natural transformation  $\llbracket \mathcal{R} \rrbracket$  from the image finite set MGSOS rules

$$(\Delta T_\Sigma)^L$$

# From MGSOS to distributive laws

$$\Sigma(Id \times \Delta^L)$$

$$\Downarrow \llbracket \mathcal{R} \rrbracket$$

$$(\mathcal{P}_{\text{fin}} T_M \Delta)^L$$

$$\Downarrow (\mathcal{P}_{\text{fin}} \langle \cdot \rangle)^L$$

$$(\mathcal{P}_{\text{fin}} \Delta T_\Sigma)^L$$

$$(\Delta T_\Sigma)^L$$

1. define the natural transformation  $\llbracket \mathcal{R} \rrbracket$   
from the image finite set MGSOS rules

2. apply the measure terms interpretation

$$\langle \cdot \rangle: T_M \Delta \Rightarrow \Delta T_\Sigma$$

# From MGSOS to distributive laws

$$\Sigma(Id \times \Delta^L)$$

$$\Downarrow \llbracket \mathcal{R} \rrbracket$$

$$(\mathcal{P}_{\text{fin}} T_M \Delta)^L$$

$$\Downarrow (\mathcal{P}_{\text{fin}} \langle \cdot \rangle)^L$$

$$(\mathcal{P}_{\text{fin}} \Delta T_\Sigma)^L$$

$$\Downarrow (\oplus T_\Sigma)^L$$

$$(\Delta T_\Sigma)^L$$

1. define the natural transformation  $\llbracket \mathcal{R} \rrbracket$   
from the image finite set MGSOS rules

2. apply the measure terms interpretation

$$\langle \cdot \rangle: T_M \Delta \Rightarrow \Delta T_\Sigma$$

3. obtain the actual measure by averaging

$$\oplus_X(\{\mu_1, \dots, \mu_n\})(E) = \frac{\mu_1(E) + \dots + \mu_n(E)}{\mu_1(X) + \dots + \mu_n(X)}$$

# Benefits from the bialgebraic framework

For continuous state probabilistic processes described by means of MGSOS specification systems we have:

- + denotational model on the final  $\Delta^L$ -coalgebra
- + operational model on the initial  $\Sigma$ -algebra
  
- + universal semantics (full-abstraction)
  - initial algebra semantics = final coalgebra semantics
- +  $\Delta^L$ -behavioural equivalence is a  $\Sigma$ -congruence
- + is  $\Delta^L$ -bisimilarity a  $\Sigma$ -congruence?
  - ( $\Delta^L$  does not preserve weak pullbacks! [Viglizzo'05])

# From MGSOS to distributive laws

$$\begin{array}{c} \Sigma(Id \times \Delta^L) \\ \Downarrow [\mathcal{R}] \\ (\mathcal{P}_{\text{fin}} T_M \Delta)^L \\ \Downarrow (\mathcal{P}_{\text{fin}} \Downarrow \cdot \Downarrow)^L \\ (\mathcal{P}_{\text{fin}} \Delta T_\Sigma)^L \\ \Downarrow (\oplus T_\Sigma)^L \\ (\Delta T_\Sigma)^L \end{array}$$

Naturality of the distributive laws depends on naturality of  $\Downarrow \cdot \Downarrow: T_M \Delta \Rightarrow \Delta T_\Sigma$

**we need (general) techniques  
in order to derive  
natural transformations of type**

$$T_M \Delta \Rightarrow \Delta T_\Sigma$$

We adopt a generalized induction proof principle...

For any distributive law  $\lambda: SB \Rightarrow BS$  and  $SB$ -algebra  $(X, \varphi)$  there exists a unique  $f: A \rightarrow X$  making the following commute

$$\begin{array}{ccc} SBX & \xleftarrow{SBf} & SBA & \xleftarrow{S\beta_\lambda} & SA \\ \varphi \downarrow & & & & \downarrow \alpha \\ X & \xleftarrow{\quad f \quad} & A & & \end{array} \qquad \begin{array}{ccccc} SA & \xrightarrow{\alpha} & A & \xrightarrow{\beta_\lambda} & BA \\ S\beta_\lambda \downarrow & & & & \uparrow B\alpha \\ SBA & \xrightarrow{\quad \lambda_A \quad} & & & BSA \end{array}$$

# Structural $\lambda$ -iterative recursion

... can be extended on the free monad  $(T_S, \eta^S, \mu^S)$

$$\begin{array}{ccccc}
 SBY & \xleftarrow{SBf} & SBT_S X & \xleftarrow{S\beta_\lambda} & ST_S X \\
 \downarrow \varphi & & & & \downarrow \psi_X \\
 Y & \xleftarrow{\quad f \quad} & T_S X & & \\
 & \nearrow \phi & \uparrow \eta_X^S & & X
 \end{array}$$

$$\begin{array}{ccccc}
 X & \xrightarrow{\eta_X^S} & T_S X & \xleftarrow{\psi_X} & ST_S X \\
 \downarrow k & & \downarrow \beta_\lambda & & \downarrow S\beta_\lambda \\
 BX & \xrightarrow{B\eta_X^S} & BT_S X & \xleftarrow{B\psi_X \circ \lambda_{T_S X}} & SBT_S X
 \end{array}$$

... and can be turned to a proof principle on natural transformations

$$\begin{array}{ccccc}
 SBF & \xleftarrow{SBf} & SBT_S & \xleftarrow{S\beta_\lambda} & ST_S \\
 \varphi \Downarrow & & & & \Downarrow \psi \\
 F & \xleftarrow{f} & T_S & & \\
 & \searrow \phi & & & \Uparrow \eta^s \\
 & & Id & & \\
 \\ 
 Id & \xrightarrow{\eta^s} & T_S & \xleftarrow{\psi} & ST_S \\
 k \Downarrow & & \beta_\lambda \Downarrow & & \Downarrow S\beta_\lambda \\
 B & \xrightarrow{B\eta^s} & BT_S & \xleftarrow{B\psi \circ \lambda T_S} & SBT_S
 \end{array}$$



... to be used to derive measure terms interpretations

$$\begin{array}{ccccc}
 MB\Delta T_\Sigma & \xleftarrow{MB\langle \cdot \rangle} & MBT_M\Delta & \xleftarrow{M\beta_\lambda\Delta} & MT_M\Delta \\
 \varphi \Downarrow & & \langle \cdot \rangle & & \Downarrow \psi^m\Delta \\
 \Delta T_\Sigma & \xleftarrow{\langle \cdot \rangle} & T_M\Delta & & \\
 & & & & \Uparrow \eta^m\Delta \\
 & & & & \Delta \\
 & & \phi & & 
 \end{array}$$

$$\begin{array}{ccccc}
 Id & \xrightarrow{\eta^m} & T_M & \xleftarrow{\psi^m} & MT_M \\
 k \Downarrow & & \beta_\lambda \Downarrow & & \Downarrow M\beta_\lambda \\
 B & \xrightarrow{B\eta^m} & BT_M & \xleftarrow{B\psi^m \circ \lambda T_M} & MBT_M
 \end{array}$$

# Conclusions and future work

## Done:

- + rule format for continuous state probabilistic processes
- + syntactical treatment of measures via  $M$ -terms
- + general techniques for defining interpretations
- + initial algebra for polynomial functors in **Meas** (not in this talk)

## To do:

- + move from probabilistic to general measures (bounded?)
- + find a rule format that coincides with the distributive law
- + formal expressivity analysis of the intermediate syntax + interpretation method

**Thanks**

# Appendix

# Bisimulation vs Kernel-bisimulation

## Bisimulation

(a span)

$$\begin{array}{ccccc} X & \xleftarrow{f} & R & \xrightarrow{g} & Y \\ \alpha \downarrow & & \downarrow \gamma & & \downarrow \beta \\ BX & \xleftarrow{Bf} & BR & \xrightarrow{Bg} & BY \end{array}$$

## Kernel-bisimulation

(pullback of a cospan)

$$\begin{array}{ccccc} & & R & & \\ & \swarrow \pi_1 & \vee & \searrow \pi_2 & \\ X & \xrightarrow{f} & C & \xleftarrow{g} & Y \\ \alpha \downarrow & & \downarrow \gamma & & \downarrow \beta \\ BX & \xrightarrow{Bf} & BC & \xleftarrow{Bg} & BY \end{array}$$

if  $B$  preserves weak-pullbacks, bisimulation and kernel-bisimulation coincide (provided that  $\mathbf{C}$  has pullbacks and pushouts) [Staton'11]