



*ASL 2013 - University of Waterloo  
8-11 May*



## **Probabilistic Coherent Spaces vs Probabilistic PCF A Full Abstraction Result.**

joint work with **Thomas Ehrhard** and **Michele Pagani**

**Christine Tasson**

`Christine.Tasson@pps.univ-paris-diderot.fr`

**Laboratoire PPS - Université Paris Diderot**

## An example of Randomized Algorithm

- Formalize its syntax.
- Reason on its semantics.

## A Full Abstraction Result in a Probabilistic Setting

- Semantics : PCoh, Probabilistic Coherent Spaces [Girard04]
- Syntax : PPCF, a Probabilistic extension of PCF [Plotkin77]

## Derivation, the key stone of Probabilistic Full Abstraction

- Taylor expansion
- Well-pointedness and derivation

## Full Abstraction :

**A Bridge between Syntax and Semantics.**

« *Decide what you want to say before you worry how you are going to say it.* »      The Scott-Strachey Approach to Programming Language Theory, preface, Scott (77)

## Denotational semantics :

a program as a function between mathematical spaces

## Operational semantics :

a program as a sequence of computation steps

« *Full Abstraction studies connections between denotational and operational semantics.* »      LCF Considered as a Programming Language, Plotkin (77)

## FA relates Semantical and Observational equivalences :

$$\begin{array}{ccc}
 \llbracket P \rrbracket = \llbracket Q \rrbracket & \begin{array}{c} \text{Adequacy} \\ \Rightarrow \\ \Leftarrow \\ \text{Full Completeness} \end{array} & P \simeq_o Q \\
 & & (\forall C[\cdot], C[P] \rightarrow^* v \iff C[Q] \rightarrow^* v)
 \end{array}$$

## How to prove Full Completeness :

- ① By **contradiction**, start with  $\llbracket P \rrbracket \neq \llbracket Q \rrbracket$
- ② Find **testing function** :  $f$  such that  $f\llbracket P \rrbracket \neq f\llbracket Q \rrbracket$
- ③ Prove **definability** :  
 $\exists C[\cdot], \forall P, f\llbracket P \rrbracket = \llbracket C[P] \rrbracket$  and  $C[P] \rightarrow p$ .
- ④ Conclude :  
 $\exists C[\cdot], \llbracket C[P] \rrbracket \neq \llbracket C[Q] \rrbracket \Rightarrow p \neq q \Rightarrow P \not\simeq_o Q$ .

**Randomized algorithm :**

**A Las Vegas example.**

# An example of Randomized algorithm

**Input :** A 0/1 array of length  $n \geq 2$  in which half cells are 0.

<u>0</u>	<u>1</u>	<u>0</u>	<u>1</u>	<u>1</u>	<u>0</u>
----------	----------	----------	----------	----------	----------

 $f : 0, 1, 5 \mapsto \underline{0}, \quad 1, 2, 3 \mapsto \underline{1}$

**Output :** Find the index of a cell containing 0.

```
let rec LasVegas (f: nat -> nat) (n:nat) =  
  let k = random n in  
    if (f k = 0) then k  
    else LasVegas f n
```

**This algorithm succeeds with probability one.**

- Success in 1 step is :  $\frac{1}{2}$ .
- Success in 2 steps is :  $\frac{1}{2^2}$ .
- Success in  $n$  steps is :  $\frac{1}{2^n}$ .

Success in any steps is :

$$\sum_{k=1}^{\infty} \frac{1}{2^k} = 1.$$

## Modeling Probabilistic Data and Programs :

**Type** : set of positive vectors

**Program** : function seen as a positive matrix

**Interaction** : composition seen as multiplication



## Example : nat

**Coin**: nat returns the toss of a fair coin.

**Random n**: nat returns uniformly any  $\{0, \dots, n-1\}$ .

**Non Determinism, a first approximation** :  $|\text{nat}| = \mathbb{N}$ .

$$|\text{Coin}| = \{0, 1\} \quad \text{and} \quad |\text{Random } n| = \{0, \dots, n-1\}$$

**Enriching with positive coefficients** :  $\llbracket \text{nat} \rrbracket \subseteq (\mathbb{R}^+)^{\mathbb{N}}$ .

$$\llbracket \text{Coin} \rrbracket = \left( \begin{array}{cccc} \frac{1}{2} & \frac{1}{2} & 0 & \dots \\ \downarrow & \downarrow & \downarrow & \dots \\ 0 & 1 & 2 & \dots \end{array} \right) \quad \text{and} \quad \llbracket \text{Random } n \rrbracket = \left( \begin{array}{cccc} \frac{1}{n} & \dots & \frac{1}{n} & 0 & \dots \\ \downarrow & & \downarrow & & \dots \\ 0 & \dots & n-1 & & \dots \end{array} \right)$$

**Subprobability Distributions over  $\mathbb{N}$**  :

$$\llbracket \text{nat} \rrbracket = \left\{ (\lambda_n)_{n \in \mathbb{N}} \mid \forall n, \lambda_n \in \mathbb{R}^+ \text{ and } \sum_n \lambda_n \leq 1 \right\}$$

**Example :**  $\text{Random} : \text{nat} \rightarrow \text{nat}$

Input : an integer  $n$

Output : any integer  $\{0, \dots, n - 1\}$  uniformly chosen.

**Non Determinism :**  $|\text{Random}| \subseteq |\text{nat}| \times |\text{nat}|$  is a relation.

$$|\text{Random}| = \{(n, k) \mid n \in \mathbb{N}, k \in \{0, \dots, n - 1\}\}$$

**Enriching with positive coefficients :**  $\llbracket \text{Random} \rrbracket \in (\mathbb{R}^+)^{(\mathbb{N} \times \mathbb{N})}$ .

$$\begin{pmatrix} \begin{matrix} \downarrow 1 \\ 1 \end{matrix} & \begin{matrix} \downarrow 2 \\ \frac{1}{2} \end{matrix} & \dots & \begin{matrix} \downarrow n \\ \frac{1}{n} \end{matrix} & \dots \\ 0 & \frac{1}{2} & \dots & \frac{1}{n} & \dots \\ \vdots & 0 & \ddots & \vdots & \\ & \vdots & 0 & \frac{1}{n} & \\ & & \vdots & \ddots & \ddots \end{pmatrix} \begin{matrix} \rightarrow 0 \\ \rightarrow 1 \\ \vdots \\ \rightarrow n-1 \\ \vdots \end{matrix}$$

# Modeling Probabilistic Programs

Once :  $\text{nat} \rightarrow \text{nat}$

Input : an integer n

Output : if n=0 then 42  
          else Coin

$$\begin{array}{cccc}
 0 & 1 & \dots & \dots \\
 \downarrow & \downarrow & & \\
 \left( \begin{array}{cccc}
 0 & \frac{1}{2} & \frac{1}{2} & \dots \\
 0 & \frac{1}{2} & \frac{1}{2} & \dots \\
 0 & 0 & 0 & \dots \\
 \dots & 0 & \dots & \ddots \\
 1 & 0 & \dots & \\
 \dots & 0 & \dots & \ddots
 \end{array} \right) & \begin{array}{l} \rightarrow 0 \\ \rightarrow 1 \\ \vdots \\ \vdots \\ \rightarrow 42 \\ \vdots \end{array}
 \end{array}$$

Twice :  $\text{nat} \rightarrow \text{nat}$

Input : an integer n

Output : if n=0 then 42  
          else Random n

$$\begin{array}{ll}
 ([0], 42) & \mapsto 1 \\
 ([n_1, n_2], k) & \mapsto \frac{1}{n_1} + \frac{1}{n_2} \\
 & \text{if } 0 \leq k \leq n_1 - 1 \leq n_2 - 1 \\
 ([n_1, n_2], k) & \mapsto \frac{1}{n_2} \\
 & \text{if } n_1 - 1 < k \leq n_2 - 1 \\
 \text{Otherwise} & 0
 \end{array}$$

## Probabilistic Data :

If  $x : \text{nat}$ , then  $\llbracket x \rrbracket = (x_n)_{n \in \mathbb{N}}$

where  $x_n$  is the probability that  $x$  is  $n$ .

## Probabilistic Program : $P : \text{nat} \rightarrow \text{nat}$

where  $\llbracket P x \rrbracket_n$  is the probability that  $P x$  computes  $n$ .

$$\llbracket \text{Once} \rrbracket \in (\mathbb{R}^+)^{\mathbb{N} \times \mathbb{N}}$$

$$\llbracket \text{Twice} \rrbracket \in (\mathbb{R}^+)^{\mathcal{M}_{\text{fin}}(\mathbb{N}) \times \mathbb{N}}$$

$$\begin{aligned} \llbracket \text{Once } x \rrbracket_n &= \llbracket \text{Once} \rrbracket \cdot \llbracket x \rrbracket \\ &= \sum_k \llbracket \text{Once} \rrbracket_{(k,n)} \llbracket x \rrbracket_k \end{aligned}$$

$$\begin{aligned} \llbracket \text{Twice } x \rrbracket_n &= \llbracket \text{Twice} \rrbracket \cdot \llbracket x \rrbracket^! \\ &= \sum_{\mu} \llbracket \text{Twice} \rrbracket_{(\mu,n)} \prod_{k \in \mu} \llbracket x \rrbracket_k \end{aligned}$$

Syntax :

**probabilistic PCF**

# A Typed Probabilistic Functional Programming Language

Types :

$\sigma, \tau = \text{nat} \mid \sigma \Rightarrow \tau$

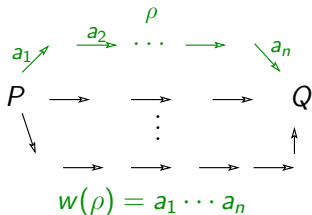
Probabilistic PCF :

$N, P, Q := \underline{n} \mid \text{pred}(N) \mid \text{succ}(N) \mid x \mid \lambda x^\sigma P \mid (P)Q \mid \text{fix}(M)$   
 $\mid \text{if } (N = \underline{0}) \text{ then } P \text{ else } Q \mid a \cdot P + b \cdot Q, \text{ when } a + b \leq 1$

Operational Semantics :

$P \xrightarrow{a} Q$

$P$  reduces to  $Q$  in one step with probability  $a$



if  $(\underline{0} = \underline{0})$  then  $P$  else  $Q \xrightarrow{1} P$

if  $(\underline{n+1} = \underline{0})$  then  $P$  else  $Q \xrightarrow{1} Q$

$a \cdot P + b \cdot Q \xrightarrow{a} P$

$\text{Proba}(P \xrightarrow{*} Q) = \sum_{\rho} w(\rho)$

## Caml encoding :

```

let rec LasVegas (f:nat->nat) (n:nat) =
  let k = random n in
  if (f k = 0) then k
  else LasVegas f n

```

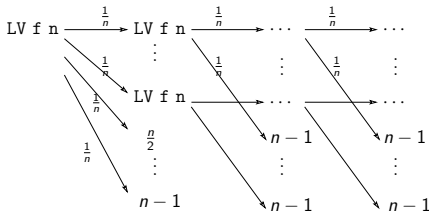
## PCF encoding :

$$\text{fix } (\lambda \text{LasVegas}^{(\text{nat} \Rightarrow \text{nat}) \Rightarrow \text{nat} \Rightarrow \text{nat}}
 \lambda f^{\text{nat} \Rightarrow \text{nat}} \lambda n^{\text{nat}}
 \left( \frac{1}{n} \lambda g^{\text{nat} \Rightarrow \text{nat}} g \underline{0} + \dots + \frac{1}{n} \lambda g^{\text{nat} \Rightarrow \text{nat}} g \underline{n-1} \right)
 \lambda k^{\text{nat}} \text{ if } (f k = \underline{0}) \text{ then } k
 \text{ else LasVegas } f \ n)$$

## PCF encoding :

$\mathbf{fix} \left( \lambda \text{ LasVegas}^{(\text{nat} \Rightarrow \text{nat}) \Rightarrow \text{nat} \Rightarrow \text{nat}} \right.$   
 $\quad \lambda f^{\text{nat} \Rightarrow \text{nat}} \lambda n^{\text{nat}}$   
 $\quad \left( \frac{1}{n} \lambda g^{\text{nat} \Rightarrow \text{nat}} g \ \underline{1} + \dots + \frac{1}{n} \lambda g^{\text{nat} \Rightarrow \text{nat}} g \ \underline{n} \right)$   
 $\quad \lambda k^{\text{nat}} \ \mathbf{if} \ (f \ k = \underline{0}) \ \mathbf{then} \ k$   
 $\quad \quad \mathbf{else} \ \text{LasVegas } f \ n)$

## Operational Semantics :





## Quantitative Semantics :

### Probabilistic Coherent Spaces (Pcoh)

Types (Object) : representing randomized data : nat, ...

Programs (Maps) : Input Type  $\rightarrow$  Output Type

Interaction (Composition):

Input Type  $\xrightarrow{P}$  Intermediate Type  $\xrightarrow{Q}$  Output Type

**Orthogonality :**

$$x, y \in (\mathbb{R}^+)^{|\sigma|}.$$

$$x \perp y \iff \sum_{a \in |\sigma|} x_a y_a \in [0, 1].$$

Given a set  $P \subseteq (\mathbb{R}^+)^{|\sigma|}$  we define  $P^\perp$ , the *orthogonal* of  $P$ , as

$$P^\perp := \{y \in (\mathbb{R}^+)^{|\sigma|} \mid \forall x \in P \langle x, y \rangle \leq 1\}.$$

**Probabilistic Coherent Space :**

$$\mathcal{X} = (|\mathcal{X}|, P(\mathcal{X}))$$

where  $|\mathcal{X}|$  is a countable set  
and  $P(\mathcal{X}) \subseteq (\mathbb{R}^+)^{|\mathcal{X}|}$

such that the following holds :

**closedness :**  $P(\mathcal{X})^{\perp\perp} = P(\mathcal{X})$ ,

**boundedness :**  $\forall a \in |\mathcal{X}|, \exists \mu > 0, \forall x \in P(\mathcal{X}), x_a \leq \mu$ ,

**completeness :**  $\forall a \in |\mathcal{X}|, \exists \lambda > 0, \lambda e_a \in P(\mathcal{X})$ .

**Objects of PCoh :**

$$\mathcal{X} = (|\mathcal{X}|, P(\mathcal{X}))$$

where  $|\mathcal{X}|$  is a countable set  
and  $P(\mathcal{X}) \subseteq (\mathbb{R}^+)^{|\mathcal{X}|}$

**Type Example :**

$$\llbracket \mathbf{nat} \rrbracket = (\mathbb{N}, P(\mathbf{nat}) = \{(\lambda_n) \mid \sum_n \lambda_n \leq 1\})$$

**Data Example :**

if  $M : \mathbf{nat}$ , then  $\llbracket M \rrbracket \in P(\mathbf{nat}) \subseteq (\mathbb{R}^+)^{\mathbb{N}}$   
is a subprobability distributions.

**Coin :**

$$\frac{1}{2} \cdot \underline{0} + \frac{1}{2} \cdot \underline{1}$$

$$\llbracket \mathbf{Coin} \rrbracket = \left(\frac{1}{2}, \frac{1}{2}, 0, \dots\right)$$

Maps of PCoh :

$$f : (|\mathcal{X}|, P(\mathcal{X})) \rightarrow (|\mathcal{Y}|, P(\mathcal{Y}))$$

defined as a **matrix**  $M(f) \in (\mathbb{R}^+)^{\mathcal{M}_{\text{fin}}(|\mathcal{X}|) \times |\mathcal{Y}|}$

thanks to **Taylor formula** :

$$f(x) = \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} M(f)_{\mu} \cdot x^{\mu}$$

$$\text{with } x^{\mu} = \prod_{a \in \text{Supp}(x)} x_a^{\mu(a)}$$

$f$  can be seen as an **entire function**  $f : (\mathbb{R}^+)^{|\mathcal{X}|} \rightarrow (\mathbb{R}^+)^{|\mathcal{Y}|}$   
**preserving** probabilistic coherence,  $f(P(\mathcal{X})) \subseteq P(\mathcal{Y})$

**Example** :

if  $P : \text{nat} \rightarrow \text{nat}$ , then  $\llbracket P \rrbracket : (\mathbb{R}^+)^{\mathbb{N}} \rightarrow (\mathbb{R}^+)^{\mathbb{N}}$   
is an entire function preserving subprobability distributions.

**Once : nat  $\rightarrow$  nat**

$\lambda n$  if  $n=0$  then 42 else Coin

$$\llbracket \text{Once} \rrbracket(x)_0 = \frac{1}{2} \sum_{n \geq 1} x_n$$

$$\llbracket \text{Once} \rrbracket(x)_1 = \frac{1}{2} \sum_{n \geq 1} x_n$$

$$\llbracket \text{Once} \rrbracket(x)_{42} = x_0$$

**Twice : nat  $\rightarrow$  nat**

$\lambda n$  if  $n=0$  then 42 else Random  $n$

$$\llbracket \text{Twice} \rrbracket(x)_k = \sum_{p=1}^k \sum_{q \geq k+1} \frac{1}{q} x_p x_q + \sum_{p=1}^{k+1} \sum_{q \geq k+1} \left(\frac{1}{p} + \frac{1}{q}\right) x_p x_q, \text{ if } k \neq 42$$

$$\llbracket \text{Twice} \rrbracket(x)_{42} = x_0 + \sum_{p=1}^{42} \sum_{q \geq 43} \frac{1}{q} x_p x_q + \sum_{p=1}^{43} \sum_{q \geq 43} \left(\frac{1}{p} + \frac{1}{q}\right) x_p x_q$$

**A model of PPCF :**

in particular, **PCoh** is a model of differential linear logic.

**Compositionality :**

For  $C : \sigma \Rightarrow \tau, P : \sigma,$

$$\llbracket (C)P \rrbracket_- = \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} \llbracket C \rrbracket_{\mu, -} \llbracket P \rrbracket^{\mu}$$

**Adequacy Lemma :**

Let  $M : \text{nat}$  be a closed program. Then for all  $n,$

$$\text{Proba}(M \xrightarrow{*} \underline{n}) = \llbracket M \rrbracket_n.$$

**LasVegas f n : nat**

$$\text{Proba}(\text{LasVegas f n} \rightarrow^* \bullet) = \sum_k \llbracket \text{LasVegas f n} \rrbracket_k = 1$$

## Probabilistic Full Abstraction :

### The completeness theorem

**FA relates Semantical and Observational equivalences :**

Let  $P, Q : \sigma \quad \forall \alpha \in |\sigma|, \llbracket P \rrbracket_\alpha = \llbracket Q \rrbracket_\alpha$

Adequacy  $\Downarrow \Uparrow$  Full Completeness

$\forall C : \sigma \Rightarrow \text{nat}, \forall n \in |\text{nat}|,$   
 $\text{Proba}((C)P \xrightarrow{*} n) = \text{Proba}((C)Q \xrightarrow{*} n)$

**Adequacy proof :**

- ① Apply **Adequacy Lemma** :  $\forall n, \text{Proba}((C)P \xrightarrow{*} n) = \llbracket (C)P \rrbracket_n$ .
- ② Apply **Compositionality** :

$$\forall n, \llbracket (C)P \rrbracket_n = \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} \llbracket C \rrbracket_{\mu, n} \prod_{\alpha \in \mu} \llbracket P \rrbracket_\alpha^{\mu(\alpha)}$$



## FA relates Semantical and Observational equivalences :

Let  $P, Q : \sigma \quad \forall \alpha \in |\sigma|, \llbracket P \rrbracket_\alpha = \llbracket Q \rrbracket_\alpha$

Adequacy  $\Downarrow \Uparrow$  Full Completeness

$\forall C : \sigma \Rightarrow \text{nat}, \forall n \in |\text{nat}|,$   
 $\text{Proba}((C)P \xrightarrow{*} n) = \text{Proba}((C)Q \xrightarrow{*} n)$

## Adequacy proof :

- ① Apply Adequacy Lemma :  $\forall n, \text{Proba}((C)P \xrightarrow{*} n) = \llbracket (C)P \rrbracket_n$ .
- ② Apply Compositionality :

$$\begin{aligned} \forall n, \llbracket (C)P \rrbracket_n &= \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} \llbracket C \rrbracket_{\mu, n} \prod_{\alpha \in \mu} \llbracket P \rrbracket_\alpha^{\mu(\alpha)} \\ &= \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} \llbracket C \rrbracket_{\mu, n} \prod_{\alpha \in \mu} \llbracket Q \rrbracket_\alpha^{\mu(\alpha)} = \llbracket (C)Q \rrbracket_n \end{aligned}$$

## FA relates Semantical and Observational equivalences :

Let  $P, Q : \sigma \quad \forall \alpha \in |\sigma|, \llbracket P \rrbracket_\alpha = \llbracket Q \rrbracket_\alpha$

Adequacy  $\Downarrow \Uparrow$  Full Completeness

$\forall C : \sigma \Rightarrow \text{nat}, \forall n \in |\text{nat}|,$   
 $\text{Proba}((C)P \xrightarrow{*} n) = \text{Proba}((C)Q \xrightarrow{*} n)$

## Full Completeness proof :

- ① By **contradiction** :  $\exists \alpha \in |\sigma|, \llbracket P \rrbracket_\alpha \neq \llbracket Q \rrbracket_\alpha$
- ② Find **testing context** :  $T_\alpha$  such that  $\llbracket (T_\alpha)P \rrbracket_0 \neq \llbracket (T_\alpha)Q \rrbracket_0$
- ③ Prove **definability** :  $T_\alpha \in \text{PPCF}$
- ④ Apply **Adequacy** :  
 $\text{Proba}((T_\alpha)P \xrightarrow{*} 0) \neq \text{Proba}((T_\alpha)Q \xrightarrow{*} 0).$

## Assumptions

- $P, Q : \text{nat}$
- $\llbracket P \rrbracket_n \neq \llbracket Q \rrbracket_n$

## Goal

- $T_n : \text{nat} \rightarrow \text{nat}$
- $\llbracket (T_n)P \rrbracket_0 \neq \llbracket (T_n)Q \rrbracket_0$

## Choose

If  $T_n = \lambda x^{\text{nat}} \text{ if } (x = \underline{n}) \text{ then } \underline{0}$       Then       $\llbracket T_n \rrbracket_{[n],0} = 1$

## Conclude

By Compositionality,  $\llbracket (T_n)P \rrbracket_0 = \llbracket P \rrbracket_n \neq \llbracket Q \rrbracket_n = \llbracket (T_n)Q \rrbracket_0$

# Find a testing context : Induction Case

## Assumptions

- $P, Q : \phi \Rightarrow \psi$
- $\alpha = ([\gamma_1, \dots, \gamma_n], \beta)$
- $\llbracket P \rrbracket_\alpha \neq \llbracket Q \rrbracket_\alpha$

## Goal

- $T_\alpha : (\phi \Rightarrow \psi) \rightarrow \text{nat}$
- $\llbracket (T_\alpha)P \rrbracket \neq \llbracket (T_\alpha)Q \rrbracket$
- $\llbracket T_\alpha \rrbracket_\mu \neq 0 \Leftrightarrow \mu = [\alpha]$

## Compositionality

$$\llbracket (T_\alpha)P \rrbracket = \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} \llbracket T_\alpha \rrbracket_\mu \prod_{\delta \in \mu} \llbracket P \rrbracket_\delta^{\mu(\delta)}$$

## Choose

$$T_\alpha(\vec{X}) = \lambda f^{\phi \Rightarrow \psi} T_\beta(\vec{Y}) \left( (f) \sum_{i=1}^k \frac{L_i}{n} \mathcal{N}_{\gamma_i}(\vec{Z}'_i) \right)$$

$\mathcal{N}_\alpha(\vec{X}') = \lambda x^\phi$  if  $(\wedge_{i=1}^k T_{\gamma_i}(\vec{Z}'_i)x = \underline{0})$  then  $\mathcal{N}_\beta(\vec{Y}')$  else  $\Omega_\psi$ .

## Taylor Formula

$\forall \mu$ ,  $\llbracket T_\alpha(\vec{X}) \rrbracket_\mu$  is a power series in  $\vec{X}$   
with coeff of  $\prod \vec{X} \neq 0 \iff \mu = [\alpha]$

The coeff of  $\prod \vec{X}$  in  $\llbracket (T_\alpha(\vec{X}))P \rrbracket$  is proportional to  $\llbracket P \rrbracket_\alpha$ .

## Summary :

- The coeff of  $\llbracket \vec{X} \rrbracket$  in  $\llbracket (\mathcal{T}_\alpha(\vec{X}))P \rrbracket$  is proportional to  $\llbracket P \rrbracket_\alpha$ .
- $\llbracket P \rrbracket_\alpha \neq \llbracket Q \rrbracket_\alpha$ .
- $\llbracket (\mathcal{T}_\alpha(\vec{X}))P \rrbracket$  and  $\llbracket (\mathcal{T}_\alpha(\vec{X}))Q \rrbracket$  are two real power series with different coefficients.

## Definability :

Find  $\vec{\lambda} \in [0, 1]^{(\mathbb{N})}$  then  $\mathcal{T}_\alpha(\vec{\lambda})$  in ProbaPCF  
such that  $\llbracket (\mathcal{T}_\alpha(\vec{\lambda}))P \rrbracket \neq \llbracket (\mathcal{T}_\alpha(\vec{\lambda}))Q \rrbracket$

## By contradiction :

- If they were equal, their derivatives near zero would be equal.
- Coefficients of power series are computed by **derivation** at 0.

Differential categories in use :

**Full Abstraction** from **Taylor expansion**  
and **Topological derivation**.

**Differential Operator**

$f : !X \multimap Y$

$df : X \otimes !X \multimap Y$

$$df : X \otimes !X \xrightarrow{\bar{d} \otimes -} !X \otimes !X \xrightarrow{\bar{c}} !X \xrightarrow{f} Y$$

$\begin{matrix} a & \alpha & [a] & \alpha & [a]+\alpha & \beta \end{matrix}$

**PCoh is not a differential category**

**cocontraction** does not preserve probabilistic coherence

Example :

$$[[!1]] = (\mathbb{N}, P(!1) = \{(\lambda_n) \mid \lambda_n \leq 1\})$$

$$\bar{c}(1! \otimes 1!) = (1 + 1)!$$

$$\text{with } \lambda! = (\lambda, \lambda, \dots)$$

**PCoh** is embedded in  $\mathbf{Rel}(\mathbb{R}^{+\infty})$  which is a differential category

**Pcoh is well pointed**

Derivation is topologic

Example :

if  $f :!1 \multimap 1$ , then  $\llbracket f \rrbracket : \mathbb{R}^+ \rightarrow \mathbb{R}^+$   
 such that  $f(x) = \sum_k f_k x^k$

$$df(0)(x) = \lim_{t \rightarrow 0} \frac{f(tx) - f(0)}{t}$$

**Rel( $\mathbb{R}^{+\infty}$ ) is not well pointed**

Derivation is formal

Example :

if  $g, h :!1 \multimap 1$ , then  $\llbracket g \rrbracket, \llbracket h \rrbracket : \mathbb{R}^{+\infty} \rightarrow \mathbb{R}^{+\infty}$

$$g(x) = \infty x$$

$$dg(0)(x) = \infty$$

$$h(x) = \infty x^2$$

$$dh(0)(x) = 2\infty x$$



## Sum up

- A **Probabilistic** extension of **PCF** encoding **LasVegas**
- A Quantitative semantics **Pcoh** enjoying
  - Taylor Formula :  $f(x) = \sum_{\mu \in \mathcal{M}_{\text{fin}}(|\sigma|)} M(f)_{\mu} \cdot x^{\mu}$
  - Adequacy :  $\forall n, \text{Proba}(P \xrightarrow{*} \underline{n}) = \llbracket P \rrbracket_n$ .
- **Full Abstraction** resulting from
  - Derivation
  - Well pointedness

## This is not the end of the story !

- Which models enjoy Taylor Formula ?
- Can we extend Full Abstraction to other quantitative models ?