

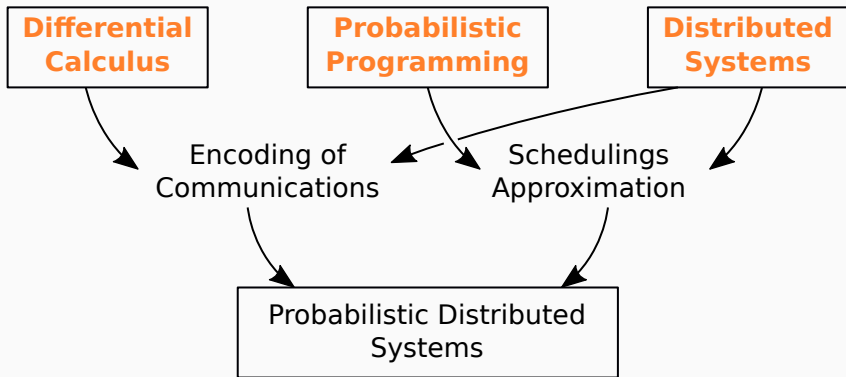


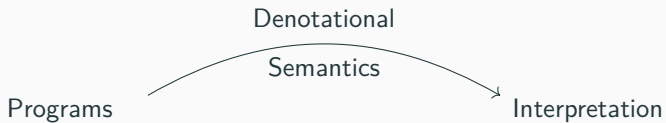
Sémantiques des Calculs Distribués, Différentiels et Probabilistes

Habilitation à diriger des recherches

Christine TASSON

23 novembre 2018

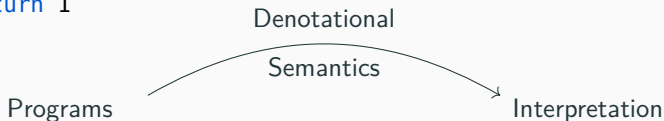






```
import random:
def flip(p):
  if random.random()<p:
    return 0
  else:
    return 1
```

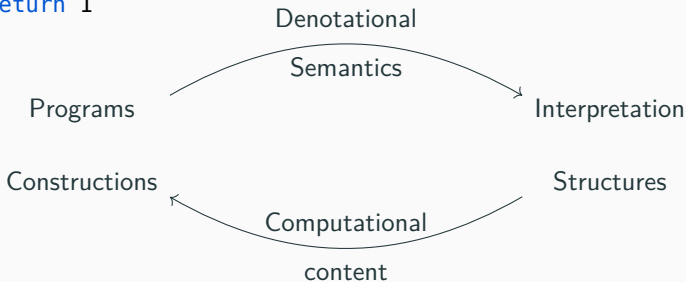
$[0, 1] \xrightarrow{f} \mathcal{V}([0, 1])$
 $0.3 \mapsto 0.3 \delta_0 + 0.7 \delta_1$





```
import random:
def flip(p):
  if random.random() < p:
    return 0
  else:
    return 1
```

$[0, 1] \xrightarrow{f} \mathcal{V}([0, 1])$
 $0.3 \mapsto 0.3 \delta_0 + 0.7 \delta_1$



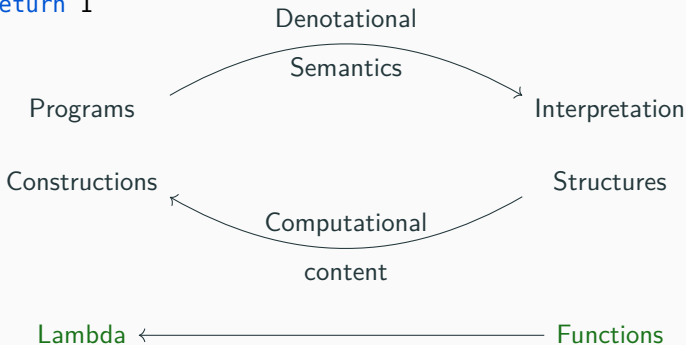
Computer Science



Mathematics

```
import random:  
def flip(p):  
    if random.random()<p:  
        return 0  
    else:  
        return 1
```

$[0, 1]$ \xrightarrow{f} $\mathcal{V}([0, 1])$
 $0.3 \mapsto 0.3 \delta_0 + 0.7 \delta_1$



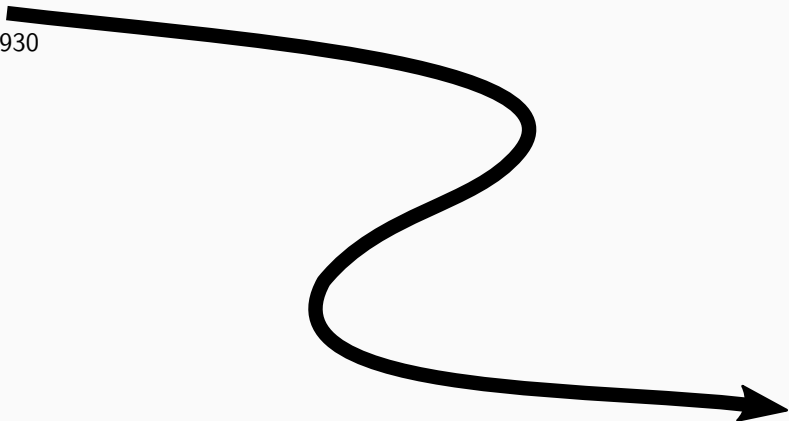
```
def shift(n):  
    return lambda s:s+n
```

Lambda-Calculus



Church

1930



Lambda-terms represent **computable functions**.

	Programs	Functions	
	M, N	$f, g : \mathbb{N} \rightarrow \mathbb{N}$	
Variable	x	x	Variable
Abstraction	$\lambda x.M$	$f : x \mapsto f(x)$	Map
Application	$(\lambda x.M)N$	$f \circ g : x \mapsto f(g(x))$	Composition



Lambda-Calculus

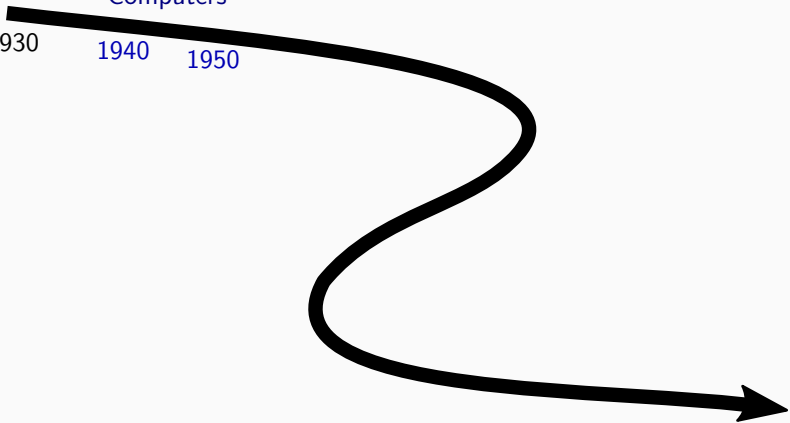
Church

Computers

1930

1940

1950





Lambda-Calculus

Church

Operational and Denotational Semantics



Landin



Strachey



Scott

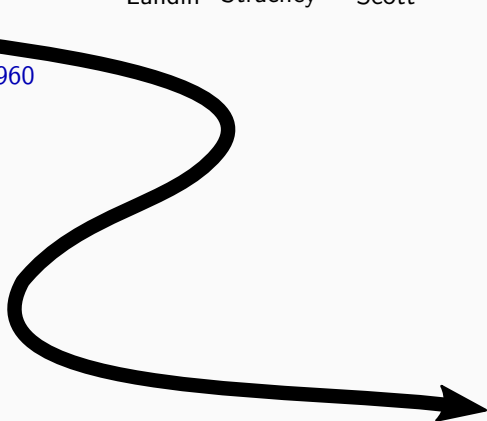
Computers

1930

1940

1950

1960



1960: From syntax to semantics

Syntax describes how to write programs,

Semantics describes how and what programs compute.

Operational semantics describes program execution as transition system. [Landin 1966]

For λ -calculus, **substitution** in contexts

$$(\lambda x.M)N \rightarrow M[N/x]$$

Denotational Semantics denotes programs as functions acting on *values* and on *memory state*. [Strachey 1960] [Scott 1969]

For pure λ -calculus, solving **equation**

$$D \stackrel{?}{=} \text{Var} + [D \rightarrow D] + \dots$$

1960: From syntax to semantics

Syntax describes how to write programs,
Semantics describes how and what programs compute.

Operational semantics describes program execution as transition system. [Landin 1966]

For λ -calculus, **substitution** in contexts

$$(\lambda x.M)N \rightarrow M[N/x]$$

Denotational Semantics denotes programs as functions acting on *values* and on *memory state*. [Strachey 1960] [Scott 1969]

For pure λ -calculus, solving **equation**

$$D \stackrel{\checkmark}{=} \text{Var} + \underbrace{[D \rightarrow D]}_{\text{Continuous}} + \dots$$

Lambda-Calculus



Church

Operational and Denotational Semantics



Landin



Strachey



Scott

Computers

1930

1940

1950

1960

1970

Proofs-Programs

Category



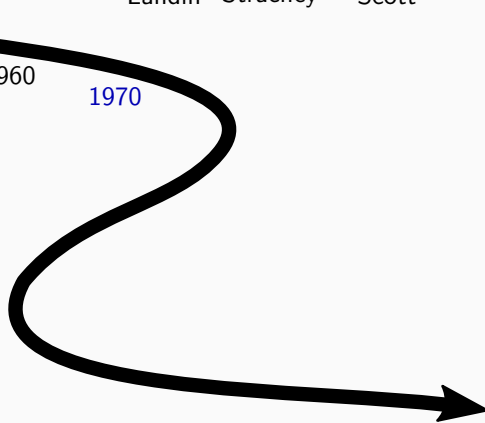
Curry



Howard



Lambek



1970: Computer Science - Logic - Category

Curry-Howard correspondence between *programs* and *proofs*

λ -calculus

Term : Type

$M : A \Rightarrow B$

Logic

Proof : Formula

$\frac{\pi}{A \Rightarrow B}$

1970: Computer Science - Logic - Category

Curry-Howard correspondence between *programs* and *proofs*

λ -calculus

Logic

Term : Type

Proof : Formula

$M : A \Rightarrow B$

$\frac{\pi}{A \Rightarrow B}$

Lambek correspondence with **Cartesian Closed Categories**

Categories are made of objects and morphisms with \circ *composition*,

$[A \rightarrow B]$ Object of Morphisms from A to B



Lambda-Calculus

Church

Operational and Denotational Semantics



Landin



Strachey



Scott

Computers

1930

1940

1950

1960

Proofs-Programs

Category

1970

Stability



Berry

1980



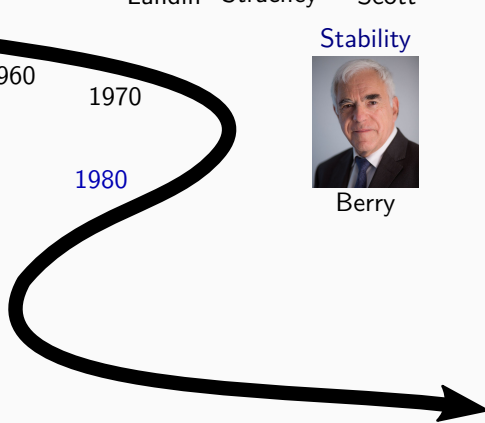
Curry



Howard



Lambek



1980: Sequential algorithms

PCF a typed functional languages such as Haskell or ML

$$M, N, P := \underbrace{x \mid \lambda x. M \mid (M) N}_{\lambda\text{-calculus}} \mid \underbrace{0 \mid \text{succ } M}_{\text{Integers}} \mid \underbrace{\text{if } M \text{ then } N \text{ else } P}_{\text{Conditional}} \mid \underbrace{\text{fix } M}_{\text{Recursion}}$$

Denotational Semantics

Scott Domains contain non sequential functions such as Parallel-Or.

Stability gets rid of this example, but does not characterize *sequentiality*

Sequential algorithm model uses the language of category [Berry-Curien 1982]

The **Full Abstraction** quest generates new models *Hypercoherence* [Ehrhard 1993] and *Game semantics* [Abramsky-Jagadeesan-Malacaria 1994], [Hyland-Ong 1995]



Lambda-Calculus

Church

Operational and Denotational Semantics



Landin

Strachey

Scott

Computers

1930

1940

1950

1960

Proofs-Programs

Category

1970

Stability



Curry

Howard

Lambek

1980



Berry

Linear Logic



Girard

1990

1990: Linear Logic

Semantical observation: [Girard 1987]

$$A \stackrel{\text{Stable}}{\Rightarrow} B \simeq !A \stackrel{\text{Linear}}{\multimap} B$$

Girard introduced new models

- **qualitative** Coherent Spaces [Girard 1986]
- **quantitative** Normal Functors [Girard 1988] and Probabilistic Coherent Spaces [Girard 2004]

Categorical models

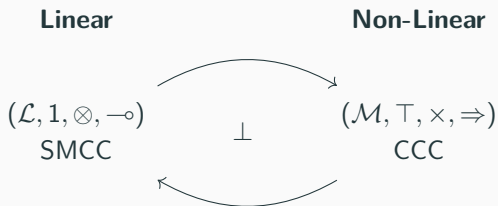


Table of contents

1. Differential λ -Calculus
2. Probabilistic Programming
3. Distributed Systems
4. Perspectives

Differential λ -Calculus

Differential Lambda Calculus

Semantical observation: in quantitative models of Linear Logic, programs are interpreted by **smooth** functions, hence **differentiation**.

[Ehrhard-Regnier 2003]

	Programs	Functions	
	M, N	f, g	
Variable	x	x	Variable
Abstraction	$\lambda x.M$	$f : x \mapsto f(x)$	Map
Application	$(\lambda x.M)N$	$f \circ g : x \mapsto f(g(x))$	Composition
Differentiation	$D\lambda x.M \cdot N$	$u, x \mapsto Df_x(u)$	Derivation

Categorical Model of Differential Lambda-Calculus

Definition 4.2 A *Cartesian (closed) differential category* is a Cartesian (closed) left-additive category having an operator $D(-)$ that maps a morphism $f : A \rightarrow B$ into a morphism $D(f) : A \times A \rightarrow B$ and satisfies the following axioms:

D1. $D(f + g) = D(f) + D(g)$ and $D(0) = 0$

D2. $D(f) \circ \langle h + k, v \rangle = D(f) \circ \langle h, v \rangle + D(f) \circ \langle k, v \rangle$ and $D(f) \circ \langle 0, v \rangle = 0$

D3. $D(\text{Id}) = \pi_1$, $D(\pi_1) = \pi_1 \circ \pi_1$ and $D(\pi_2) = \pi_2 \circ \pi_1$

D4. $D(\langle f, g \rangle) = \langle D(f), D(g) \rangle$

D5. $D(f \circ g) = D(f) \circ \langle D(g), g \circ \pi_2 \rangle$

D6. $D(D(f)) \circ \langle \langle g, 0 \rangle, \langle h, k \rangle \rangle = D(f) \circ \langle g, k \rangle$

D7. $D(D(f)) \circ \langle \langle 0, h \rangle, \langle g, k \rangle \rangle = D(D(f)) \circ \langle \langle 0, g \rangle, \langle h, k \rangle \rangle$

[Blute-Cockett-Seely 2009] [Bucciarelli-Ehrhard-Manzonetto 2010]

A **differential operator** such that if $f : A \Rightarrow B$, then $Df : A \times A \Rightarrow B$ corresponds to $u, x \mapsto Df_x(u)$ with axioms for **linearity in 1st coord.**

Categorical Model of Differential Lambda-Calculus

Definition 4.2 A *Cartesian (closed) differential category* is a Cartesian (closed) left-additive category having an operator $D(-)$ that maps a morphism $f : A \rightarrow B$ into a morphism $D(f) : A \times A \rightarrow B$ and satisfies the following axioms:

D1. $D(f + g) = D(f) + D(g)$ and $D(0) = 0$

D2. $D(f) \circ \langle h + k, v \rangle = D(f) \circ \langle h, v \rangle + D(f) \circ \langle k, v \rangle$ and $D(f) \circ \langle 0, v \rangle = 0$

D3. $D(\text{Id}) = \pi_1$, $D(\pi_1) = \pi_1 \circ \pi_1$ and $D(\pi_2) = \pi_2 \circ \pi_1$

D4. $D(\langle f, g \rangle) = \langle D(f), D(g) \rangle$

D5. $D(f \circ g) = D(f) \circ \langle D(g), g \circ \pi_2 \rangle$

D6. $D(D(f)) \circ \langle \langle g, 0 \rangle, \langle h, k \rangle \rangle = D(f) \circ \langle g, k \rangle$

D7. $D(D(f)) \circ \langle \langle 0, h \rangle, \langle g, k \rangle \rangle = D(D(f)) \circ \langle \langle 0, g \rangle, \langle h, k \rangle \rangle$

[Blute-Cockett-Seely 2009] [Bucciarelli-Ehrhard-Manzonetto 2010]

A **differential operator** such that if $f : A \Rightarrow B$, then $Df : A \times A \Rightarrow B$ corresponds to $u, x \mapsto Df_x(u)$ with axioms for **linearity in 1st coord.**

What setting for handling both linear and non-linear variables ?

using the **substitution monoidal structure** [Fiore-Plotkin-Turi 1999].

Linear Substitution

A **profunctor** $A \xrightarrow{F} B$ is a functor $A \times B^{\text{op}} \rightarrow \mathbf{Set}$,
it generalizes relations and matrices but with set coefficients.

Composition: $G \circ F(a, c) = \int^{b \in B} G(b, c) \times F(a, b)$

A **generalised species** is a profunctor $\mathcal{R} : \mathcal{L}A \rightarrow A$ where
 \mathcal{L} computes the free *Symmetric Monoidal Category* over a category A .
 $\mathcal{L}A$: sequences $\langle a_1, \dots, a_n \rangle$ and bijections and sequence of morphisms.
[Fiore-Gambino-Hyland-Winskel 2007]

As for operads, **substitution** of generalised species is described by the
composition in the Kleisli bicategory: $\mathcal{L}A \xrightarrow{\mathcal{R}} A \quad \mathcal{L}A \xrightarrow{\mathcal{R}} A$ gives a
profunctor $\mathcal{L}A \xrightarrow{\mathcal{R} \circ \mathcal{R}} A$ because \mathcal{L} lifts to profunctors
[Fiore-Gambino-Hyland-Winskel 2016]

Resource Lambda Calculus

Semantical observation: in quantitative models of Linear Logic, programs are interpreted by **series**, hence **Syntactic Taylor Expansion** approximating programs by polynomials. [Ehrhard-Regnier 2006]

	Programs	Functions
	s, t	f, g
Variable	x	x
Abstraction	$\lambda x.s$	$f : x \mapsto \sum a_n x^n$
Linear App.	$\langle \lambda x.s \rangle [t_1, \dots, t_n]$	$f \circ g : x \mapsto \sum a_n \underbrace{g(x) \cdots g(x)}_n$

Resource terms formalized as a generalised species $\mathcal{R} : \mathcal{L}A \multimap A$

$\mathcal{R}(\langle a_1, \dots, a_\ell \rangle, b)$ is the set of resource terms $x_1 : a_1, \dots, x_\ell : a_\ell \vdash s : b$

[Ong-Tsakada 2017]

Non-Linear Substitution

A **Cartesian generalised species** a profunctor $\Lambda : \mathcal{M}A \rightarrow A$ where \mathcal{M} computes the free *Cartesian Category* over a category A .

$\mathcal{M}A$: sequences $\langle \bar{a}_1, \dots, \bar{a}_n \rangle$ and functions and sequence of morphisms.

[Tanaka-Power 2004]

As for Lawvere theory, **substitution** is described by the composition in the Kleisli bicategory which is possible because \mathcal{M} also lifts to profunctors.

Lambda terms can be formalized as a cartesian generalized species.

$\Lambda(\langle \bar{b}_1, \dots, \bar{b}_n \rangle, \bar{b})$: the set of lambda terms $x_1 : \bar{b}_1, \dots, x_n : \bar{b}_n \vdash M : \bar{b}$

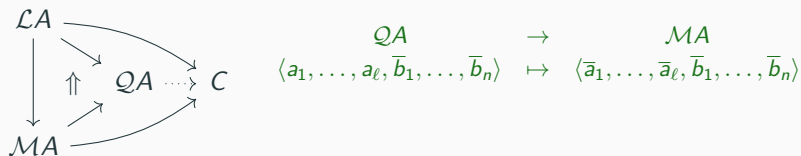
[Hyland 2017]

What construction to combine into a 2-monad lifting to profunctors ?

- \mathcal{L} free symmetric monoidal category 2-monad
 $\mathcal{L}A$: objects are sequences $\langle a_1, \dots, a_\ell \rangle$
morphisms are bijections and sequence of morphisms.
- \mathcal{M} free cartesian category 2-monad
 $\mathcal{M}A$: objects are sequences $\langle \bar{b}_1, \dots, \bar{b}_n \rangle$
morphisms are functions and sequence of morphisms.
- \mathcal{Q} Mixed linear / non linear 2-monad [Power-Tanaka 2005][Fiore 2006]
 $\mathcal{Q}A$: objects are mixed sequences $\langle a_1, \dots, a_\ell, \bar{b}_1, \dots, \bar{b}_n \rangle$
morphisms combine functions, bijections and sequence of morphisms.

Mixed Linear Non Linear Monad

Colimit in the 2-category of Symmetric Monoidal Categories.



Theorem (Hyland - Tasson)

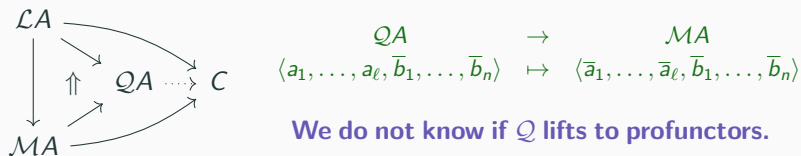
Q is a 2-monad on Symmetric Monoidal Categories.

Theorem (Hyland - Tasson)

A Q -algebra is a Symmetric Monoidal Category that splits through a Cartesian Category with coherences.

Mixed Linear Non Linear Monad

Colimit in the 2-category of Symmetric Monoidal Categories.



Theorem (Hyland - Tasson)

Q is a 2-monad on Symmetric Monoidal Categories.

Theorem (Hyland - Tasson)

A Q -algebra is a Symmetric Monoidal Category that splits through a Cartesian Category with coherences.

Contribution

- The construction of the **colimit** of 2-monads
- The **characterisation** of its algebras

Next steps

- Lift \mathcal{Q} to profunctors and describe the **substitution monoidal structure** of mixed linear/non linear variables.
- Combine the **additive** structure and encode **differential** operator

Perspectives

- Study other 2-monads appearing in semantics
- Exploit the bridge with combinatorics

Table of contents

1. Differential λ -Calculus
2. Probabilistic Programming
3. Distributed Systems
4. Perspectives

Probabilistic Programming

Study the **implementation** of probabilistic algorithms with *formal methods*: correctness, termination, behavior in context,...

Operational Semantics describes **how** probabilistic programs compute.

Denotational Semantics describes **what** probabilistic programs compute

Study the **implementation** of probabilistic algorithms with *formal methods*: correctness, termination, behavior in context,...

Operational Semantics describes **how** probabilistic programs compute.

$\mathbf{Prob}(M, N)$ is the probability that M reduces to N

- In the discrete setting, $\mathbf{Prob}(M, N)$ is a stochastic *matrix*
- In the continuous setting, $\mathbf{Prob}(M, N)$ is a stochastic *kernel*

Denotational Semantics describes **what** probabilistic programs compute

Study the **implementation** of probabilistic algorithms with *formal methods*: correctness, termination, behavior in context,...

Operational Semantics describes **how** probabilistic programs compute.

$\mathbf{Prob}(M, N)$ is the probability that M reduces to N

- In the discrete setting, $\mathbf{Prob}(M, N)$ is a stochastic *matrix*
- In the continuous setting, $\mathbf{Prob}(M, N)$ is a stochastic *kernel*

Denotational Semantics describes **what** probabilistic programs compute

$\llbracket M \rrbracket$ is a probabilistic distribution, if M is a closed ground type program

- If $\vdash M : \text{nat}$, then $\llbracket M \rrbracket$ a *discrete* distributions over integers
- If $\vdash M : \text{real}$, then $\llbracket M \rrbracket$ a *continuous* distributions over reals

Nat PPCF

Types: $A, B ::= \text{nat} \mid A \rightarrow B$

Terms: $M, N, L ::=$

$x \mid \lambda x^A.M \mid (M)N \mid \mathbf{fix}(M) \mid$

$\underline{n} \mid \mathbf{succ}(M) \mid$

$\mathbf{ifz}(L, M, N) \mid$

$\mathbf{coin} \mid \mathbf{let } x=M \mathbf{ in } N$

Operational Semantics:

$$\mathbf{Prob}(\mathbf{coin}, \underline{0}) = \frac{1}{2}$$

If $\vdash M : \text{nat}$, $\mathbf{Prob}^\infty(M, _)$ is the discrete distribution over \mathbb{N} computed by M .

Nat PPCF

Types: $A, B ::= \text{nat} \mid A \rightarrow B$

Terms: $M, N, L ::=$

$x \mid \lambda x^A.M \mid (M)N \mid \mathbf{fix}(M) \mid$

$\underline{n} \mid \mathbf{succ}(M) \mid$

$\mathbf{ifz}(L, M, N) \mid$

$\mathbf{coin} \mid \mathbf{let } x=M \mathbf{ in } N$

Operational Semantics:

$\mathbf{Prob}(\mathbf{coin}, \underline{0}) = \frac{1}{2}$

If $\vdash M : \text{nat}$, $\mathbf{Prob}^\infty(M, _)$ is the discrete distribution over \mathbb{N} computed by M .

Real PPCF

Types: $A, B ::= \text{real} \mid A \rightarrow B$

Terms: $M, N, L ::=$

$x \mid \lambda x^A.M \mid (M)N \mid \mathbf{fix}(M) \mid$

$\underline{r} \mid \underline{f}(M_1, \dots, M_n) \mid$

$\mathbf{ifz}(L, M, N) \mid$

$\mathbf{sample} \mid \mathbf{let } x=M \mathbf{ in } N$

Operational Semantics:

$\mathbf{Prob}(\mathbf{sample}, U) = \lambda_{[0,1]}(U)$

If $\vdash M : \text{real}$, $\mathbf{Prob}^\infty(M, _)$ is the continuous distribution over \mathbb{R} computed by M .

Denotational Semantics - Discrete

	Domains Semantics	Quantitative Semantics
Types	Continuous dcpos (X, \leq)	Proba. Coh. Spaces $(X , P(X) \subseteq \mathbb{R}_{>0}^{ X })$
Programs	Scott Continuous	Analytic Functions
Probability	Probabilistic monad \mathcal{V}	Values as proba. distrib.

Type:

\mathbb{N}_\perp flat domain,
 $\mathcal{V}(\mathbb{N}_\perp)$ proba. distr. over \mathbb{N}_\perp ,

Prog: $\llbracket M \rrbracket : \mathbb{N}_\perp \rightarrow \mathcal{V}(\mathbb{N}_\perp)$,
 $\llbracket \text{let } n=x \text{ in } M \rrbracket : \mathcal{V}(\mathbb{N}_\perp) \rightarrow \mathcal{V}(\mathbb{N}_\perp)$

$$x \mapsto \left(\sum_n \llbracket M \rrbracket_{n,q} x_n \right)_q$$

[Jones-Plotkin 1989]

Type:

$|\mathbf{Nat}| = \mathbb{N}$
 $P(\mathbf{Nat})$ subproba. dist. over \mathbb{N}

Prog: $\llbracket M \rrbracket : P(\mathbf{Nat}) \rightarrow P(\mathbf{Nat})$

$$x \mapsto \left(\sum_{\mu=[n_1, \dots, n_k]} \llbracket M \rrbracket_{\mu,q} \prod_{i=1}^k x_{n_i} \right)_q$$

[Danos-Ehrhard 2008]

Denotational Semantics - Continuous

Memory : measurable space and probabilistic

Programs: kernels encoding transformations of memory. [Kozen 1981]

The category **Kern** is **cartesian** but **not closed**. [Panangaden 1999]

Denotational Semantics - Continuous

Memory : measurable space and probabilistic

Programs: kernels encoding transformations of memory. [Kozen 1981]

The category **Kern** is **cartesian** but **not closed**. [Panangaden 1999]

Quasi-Borel spaces, a model of Real PPCF and recursive types based on domains and presheaves [Vakar-Kammar-Staton 2019].

Denotational Semantics - Continuous

Memory : measurable space and probabilistic

Programs: kernels encoding transformations of memory. [Kozen 1981]

The category **Kern** is **cartesian** but **not closed**. [Panangaden 1999]

Quasi-Borel spaces, a model of Real PPCF and recursive types based on domains and presheaves [Vakar-Kammar-Staton 2019].

A CCC with measurability ! [Ehrhard-Pagani-Tasson 2018]

1. **Complete cones** and Scott continuous functions
However, the category is cartesian but not closed.
2. Complete cones and **Stable functions** is cartesian closed.
However, not every stable function is measurable.
3. **Measurable Cones** (complete cones with **measurable tests**). Measurable paths pass measurable tests and **Measurable Stable functions** preserve measurable paths.

Discrete

- For $\vdash n : \mathbb{N}$,
$$\llbracket n \rrbracket_p = \delta_{p,n}$$
- For $\vdash \text{coin} : \mathbb{N}$,
$$\llbracket \text{coin} \rrbracket_p = \frac{1}{2}\delta_{0,p} + \frac{1}{2}\delta_{1,p}$$
- For $\vdash N : \mathbb{N}, \vdash P : A, \vdash Q : A$,
$$\llbracket \text{ifz}(N, P, Q) \rrbracket_a =$$
$$\llbracket N \rrbracket_0 \llbracket P \rrbracket_a + \sum_{n \neq 0} \llbracket N \rrbracket_{n+1} \llbracket Q \rrbracket_a$$
- $$\llbracket \text{let } x = N \text{ in } P \rrbracket_a =$$
$$\sum_{n=0}^{\infty} \llbracket N \rrbracket_n \widehat{\llbracket P \rrbracket}(n)_a$$

Discrete

- For $\vdash n : \mathbb{N}$,
$$\llbracket n \rrbracket_p = \delta_{p,n}$$
- For $\vdash \text{coin} : \mathbb{N}$,
$$\llbracket \text{coin} \rrbracket_p = \frac{1}{2}\delta_{0,p} + \frac{1}{2}\delta_{1,p}$$
- For $\vdash N : \mathbb{N}, \vdash P : A, \vdash Q : A$,
$$\llbracket \text{ifz}(N, P, Q) \rrbracket_a = \llbracket N \rrbracket_0 \llbracket P \rrbracket_a + \sum_{n \neq 0} \llbracket N \rrbracket_{n+1} \llbracket Q \rrbracket_a$$
- $$\llbracket \text{let } x = N \text{ in } P \rrbracket_a = \sum_{n=0}^{\infty} \llbracket N \rrbracket_n \widehat{\llbracket P \rrbracket}(n)_a$$

Continuous

- For $\vdash r : \text{real}$,
$$\llbracket r \rrbracket(U) = \delta_r(U)$$
- For $\vdash \text{sample} : \text{real}$,
$$\llbracket \text{sample} \rrbracket = \lambda_{[0,1]}(U)$$
- For $\vdash R : \text{real}, \vdash P, Q : A$,
$$\llbracket \text{ifz}(R, P, Q) \rrbracket(U) = \llbracket R \rrbracket(\{0\}) \llbracket P \rrbracket(U) + \llbracket R \rrbracket(\mathbb{R} \setminus \{0\}) \llbracket Q \rrbracket(U)$$
- $$\llbracket \text{let } x = R \text{ in } P \rrbracket(U) = \int \llbracket R \rrbracket(dr) \llbracket P \rrbracket(\delta_r)(U)$$

Invariance of semantics

- (Discrete) $\llbracket M \rrbracket = \sum_N \mathbf{Prob}(M, N) \llbracket N \rrbracket$
- (Continuous) $\llbracket M \rrbracket = \int \mathbf{Prob}(M, dt) \llbracket t \rrbracket$

Invariance of semantics

- (Discrete) $\llbracket M \rrbracket = \sum_N \mathbf{Prob}(M, N) \llbracket N \rrbracket$
- (Continuous) $\llbracket M \rrbracket = \int \mathbf{Prob}(M, dt) \llbracket t \rrbracket$

Adequacy Lemma

- (Discrete) If $\vdash M : \text{nat}$, then $\llbracket M \rrbracket_n = \mathbf{Prob}^\infty(M, \underline{n})$
- (Continuous) If $\vdash M : \text{real}$, then $\llbracket M \rrbracket(U) = \mathbf{Prob}^\infty(M, \underline{U})$

Results

Invariance of semantics

- (Discrete) $\llbracket M \rrbracket = \sum_N \mathbf{Prob}(M, N) \llbracket N \rrbracket$
- (Continuous) $\llbracket M \rrbracket = \int \mathbf{Prob}(M, dt) \llbracket t \rrbracket$

Adequacy Lemma

- (Discrete) If $\vdash M : \text{nat}$, then $\llbracket M \rrbracket_n = \mathbf{Prob}^\infty(M, \underline{n})$
- (Continuous) If $\vdash M : \text{real}$, then $\llbracket M \rrbracket(U) = \mathbf{Prob}^\infty(M, \underline{U})$

Adequacy:

If $\llbracket P \rrbracket = \llbracket Q \rrbracket$ then $P \simeq Q$ ($\mathbf{Prob}^\infty(C[P], \cdot) = \mathbf{Prob}^\infty(C[Q], \cdot)$)

- (Discrete) **Pcoh** is adequate for Nat PPCF. [Danos-Ehrhard 2008]
- (Continuous):

Theorem (Ehrhard-Pagani-Tasson 2018)

Measurable cones and **Stable** measurable functions are adequate for Real PPCF.

Results

Full Abstraction: $\llbracket P \rrbracket = \llbracket Q \rrbracket$ iff $P \simeq Q$

- (Discrete ✓) **Pcoh** is adequate for Nat PPCF. [Danos-Ehrhard 2008]

Theorems (Ehrhard-Pagani-Tasson 2018)

Probabilistic Coherent Spaces are Fully Abstract for Nat PPCF and for probabilistic Call-By-Push-Value.

Key tool: programs are interpreted as **series** thanks to quantitative semantics of LL

- (Continuous ?) We do not know if Full Abstraction holds for Measurable cones and Stable measurable functions.
The continuous case is a conservative extension of the discrete case [Crubille 2018]

Denotational semantics is a first step towards certification.

By applying **Operational Semantics, Invariance** of the denotational semantics, **Adequacy** we can prove properties of the **implementation**

- (Discrete) Rejection Sampling Algorithm
- (Continuous) Metropolis Hasting Algorithm

Rejection Sampling Algorithm

Input: A 0/1 array of length $n \geq 2$ s.t. $\frac{1}{2}$ cells are 0.

0	1	2	3	4	5	
<u>0</u>	<u>1</u>	<u>0</u>	<u>1</u>	<u>1</u>	<u>0</u>	$f : 0, 2, 5 \mapsto \underline{0}$
						$1, 3, 4 \mapsto \underline{1}$

Output: Find the index of a cell containing 0 (Success).

Implementation: $LV = \mathbf{fix}(\lambda \text{LasVegas}^{\text{nat}}. \text{let } k = \text{rand } n \text{ in}$
 $\text{ifz } (f \ k) \text{ then } k \text{ else LasVegas})$

Wanted: prove that $\mathbf{Prob}^\infty(LV, \text{Success}) = 1$

Rejection Sampling Algorithm

Implementation: $LV = \mathbf{fix}(\lambda \text{LasVegas}^{\text{nat}}. \text{let } k = \text{rand } n \text{ in}$
 $\text{ifz } (f \ k) \text{ then } k \text{ else LasVegas})$

Rejection Sampling Algorithm

Implementation: $LV = \mathbf{fix}(\lambda \text{LasVegas}^{\text{nat}}. \text{let } k = \text{rand } n \text{ in}$
 $\text{ifz } (f \ k) \text{ then } k \text{ else LasVegas})$

Operational sem.: $LV \xrightarrow{1} \text{let } k = \text{rand } n \text{ in ifz } (f \ k) \text{ then } \underline{k} \text{ else LV}$

Rejection Sampling Algorithm

Implementation: $LV = \mathbf{fix}(\lambda \text{LasVegas}^{\text{nat}}. \text{let } k = \text{rand } n \text{ in}$
 $\text{ifz } (f \ k) \text{ then } k \text{ else LasVegas})$

Operational sem.: $LV \xrightarrow{1} \text{let } k = \text{rand } n \text{ in ifz } (f \ k) \text{ then } \underline{k} \text{ else LV}$

Invariance of the semantics and interpretation of let and ifz:

$$\begin{aligned} \llbracket LV \rrbracket_p &= \sum_{k=0}^{\infty} \llbracket \text{rand } n \rrbracket_k \llbracket \text{ifz } (f \ k) \text{ then } \underline{k} \text{ else LV} \rrbracket_p \\ &= \frac{1}{n} \cdot \left(\sum_{f(k)=0, k < n} \llbracket k \rrbracket_p + \sum_{f(k) \neq 0, k < n} \llbracket LV \rrbracket_p \right) \end{aligned}$$

If $p < n$ & $f(p) = 0$, then $\llbracket LV \rrbracket_p = \frac{1}{n} + \frac{1}{n} \cdot \frac{n}{2} \cdot \llbracket LV \rrbracket_p$, so $\llbracket LV \rrbracket_p = \frac{2}{n}$.

If $p \geq n$ or $f(p) \neq 0$, then $\llbracket LV \rrbracket_p = \frac{1}{n} \cdot \frac{n}{2} \cdot \llbracket LV \rrbracket_p$, so $\llbracket LV \rrbracket_p = 0$.

Rejection Sampling Algorithm

Implementation: $LV = \mathbf{fix}(\lambda \text{LasVegas}^{\text{nat}}. \text{let } k = \text{rand } n \text{ in}$
 $\text{ifz } (f \ k) \text{ then } k \text{ else LasVegas})$

Operational sem.: $LV \xrightarrow{1} \text{let } k = \text{rand } n \text{ in ifz } (f \ k) \text{ then } \underline{k} \text{ else } LV$

Invariance of the semantics and interpretation of let and ifz:

$$\begin{aligned} \llbracket LV \rrbracket_p &= \sum_{k=0}^{\infty} \llbracket \text{rand } n \rrbracket_k \llbracket \text{ifz } (f \ k) \text{ then } \underline{k} \text{ else } LV \rrbracket_p \\ &= \frac{1}{n} \cdot \left(\sum_{f(k)=0, k < n} \llbracket \underline{k} \rrbracket_p + \sum_{f(k) \neq 0, k < n} \llbracket LV \rrbracket_p \right) \end{aligned}$$

If $p < n$ & $f(p) = 0$, then $\llbracket LV \rrbracket_p = \frac{1}{n} + \frac{1}{n} \cdot \frac{n}{2} \cdot \llbracket LV \rrbracket_p$, so $\llbracket LV \rrbracket_p = \frac{2}{n}$.

If $p \geq n$ or $f(p) \neq 0$, then $\llbracket LV \rrbracket_p = \frac{1}{n} \cdot \frac{n}{2} \cdot \llbracket LV \rrbracket_p$, so $\llbracket LV \rrbracket_p = 0$.

Adequacy Lemma, the probability that LV converges:

$$\begin{aligned} \mathbf{Prob}^{\infty}(LV, \text{Success}) &= \sum_p \mathbf{Prob}^{\infty}(LV, \underline{p}) = \sum_p \llbracket LV \rrbracket_p \\ &= \sum_{f(p)=0; p < n} \frac{2}{n} = \frac{n}{2} \cdot \frac{2}{n} = 1 \end{aligned}$$

Metropolis-Hasting Algorithm

Input: μ a distribution on \mathbb{R} with density π :
 $\mu(U) = \int_U \pi(x) dx$, but we only know $\gamma\pi$.

Output: Markov Chain x_n converging to
a random variable x with law μ

Metropolis-Hasting Algorithm

Input: μ a distribution on \mathbb{R} with density π :
 $\mu(U) = \int_U \pi(x) dx$, but we only know $\gamma\pi$.

Output: Markov Chain x_n converging to
a random variable x with law μ

Program: `MH = fix (λ MetHastnat \rightarrow nat. λn^{nat} . if n=0 then x0 else
let x = MetHast (n-1) in
let y = gauss x in
let z = bernouilli($\alpha(x,y)$) in
if z = 0 then x else y)`

Wanted: $\text{MH}(\underline{n})$ is a Markov Chain converging to a random var. of law μ .

Metropolis-Hasting Algorithm

Input: μ a distribution on \mathbb{R} with density π :
 $\mu(U) = \int_U \pi(x) dx$, but we only know $\gamma\pi$.

Output: Markov Chain x_n converging to
a random variable x with law μ

Program: $MH = \mathbf{fix}(\lambda \text{MetHast}^{\text{nat} \rightarrow \text{nat}}. \lambda n^{\text{nat}}. \text{if } n=0 \text{ then } x_0 \text{ else}$
 $\text{let } x = \text{MetHast } (n-1) \text{ in}$
 $\text{let } y = \text{gauss } x \text{ in}$
 $\text{let } z = \text{bernouilli}(\alpha(x,y)) \text{ in}$
 $\text{if } z = 0 \text{ then } x \text{ else } y)$

Wanted: $MH(\underline{n})$ is a Markov Chain converging to a random var. of law μ .

Operational Semantics:

$MH(\underline{0}) \rightarrow x_0$ thus, $\mathbf{Prob}(MH(\underline{0}), U) = \delta_{x_0}(U)$

$MH(\underline{n+1}) \rightarrow M = \text{let } x = MH(\underline{n}) \text{ in let } y = \text{gauss } x \text{ in}$

$\text{let } z = \text{bernouilli}(\alpha(x,y)) \text{ in if } z, x, y)$

Metropolis-Hasting Algorithm

```
MH(n + 1) → M = let x=MH(n) in let y=gauss x in  
let z=bernoulli(α(x, y)) in ifz(z, x, y)
```

Adequacy/Invariance/Interpretation:

$$\mathbf{Prob}(\text{MH}(\underline{n+1}), U) = \llbracket \text{MH}(\underline{n+1}) \rrbracket(U) = \llbracket M \rrbracket(U)$$

$$= \int_{\mathbb{R}} \llbracket N \rrbracket(\delta_r)(U) \llbracket \text{MH}(\underline{n}) \rrbracket(dr) = \int_{\mathbb{R}} P_{\text{MH}}(r, U) \mathbf{Prob}(\text{MH}(\underline{n}), dr)$$

$$P_{\text{MH}}(r, U) = \delta_r(U) \left(1 - \int_{\mathbb{R}} \alpha(r, t) g(t, r) \lambda(dt) \right) + \int_U \alpha(r, t) g(t, r) \lambda(dt).$$

Thus it is a Markov-Chain whose law is defined with respect to the kernel $P_{\text{MH}}(r, U)$. It is standard to prove that μ is its invariant measure.

Example

Operational Sem., Invariance and Adequacy imply Correctness

Contributions

- The study of semantics of **discrete** and **continuous** probabilistic programming
- Full Abstraction for **Probabilistic Coherent Spaces** and **Nat PPCF**
- Adequacy for **Measurable Cones and Measurable Stable functions** and **Real PPCF**
- Use of quantitative approach of LL: $\llbracket M \rrbracket = \sum \llbracket M \rrbracket_{\mu} x^{\mu}$

Next steps

- Compare with **Quasi Borel Spaces**
- Extract model of **Linear Logic** from **Measurable Cones and Measurable Stable Functions**

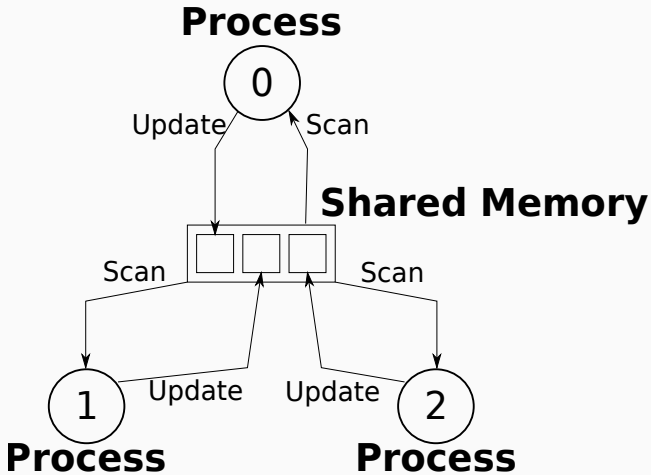
Perspectives

- Combine **differentiation** and **probability**
- **Certification** in proof assistant

Table of contents

1. Differential λ -Calculus
2. Probabilistic Programming
3. Distributed Systems
4. Perspectives

Distributed Systems



Asynchronous computations

Distributed System

A fixed family of $n + 1$ processes communicate by **Update** and **Scan** of their **local** memory into a shared **global** memory.

Asynchronous

- For each process, the k th Scan follows the k th Update
- Update and Scan are **mutually exclusive**
- no delay or order restriction

Interleaving Trace

Each execution of a protocol is given by an **interleaving trace**

$T \in \{U_i, S_i \mid i \in [n] = \{0 \cdots n\}\}^*$ well-bracketed.

Example for 3 processes, 2 rounds: $U_1 U_2 S_1 U_0 S_0 S_2 U_1 U_0 S_1 U_2 S_2 S_0$

Operational Semantics

Consider a program with $n + 1$ processes and $(r_i)_{i \in [n]}$ rounds.

State a pair $s = (\ell, m)$ where

- $\ell = (\ell_i)_{i \in [n]}$ **local** memories (one register per process)
- $m = (m_i)_{i \in [n]}$ **global** memory (one register per process)

Initial state s_0 : $\ell_i = i$ and $m_i = \perp$

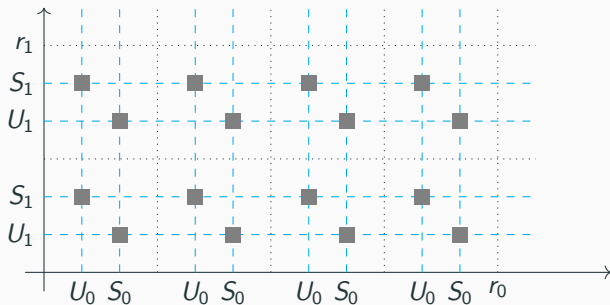
Operational Equivalence

Two interleaving traces T, T' are operationally equivalent when

$$s_0 \xrightarrow{T}^* s \quad \text{iff} \quad s_0 \xrightarrow{T'}^* s$$

Directed Algebraic Topology

$$\text{Pospace } \mathbb{X}_n = \prod_{i \in [n]} [0, r_i] \setminus \bigcup_{\substack{i, j \in [n] \\ k \in [r_i], l \in [r_j]}} U_i^k \cap S_j^l$$

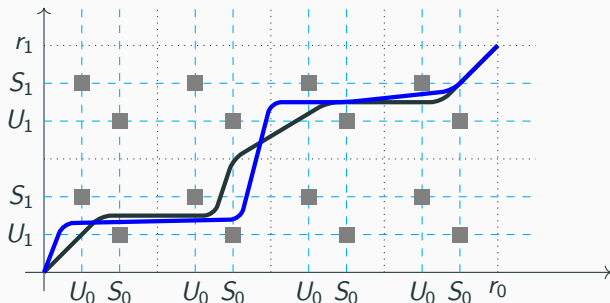


Directed Algebraic Topology

Pospace $\mathbb{X}_n = \prod_{i \in [n]} [0, r_i] \setminus \bigcup_{\substack{i, j \in [n] \\ k \in [r_i], l \in [r_j]}} U_i^k \cap S_j^l$

Dipath $\alpha : [0, 1] \rightarrow \mathbb{X}_n$ continuous and non decreasing

Dihomotopy $h : \overrightarrow{[0, 1]} \times [0, 1] \rightarrow \mathbb{X}_n$ continuous non decreasing



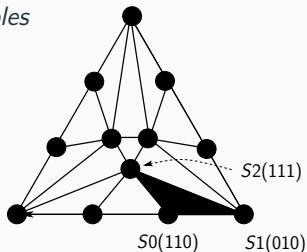
[Fajstrup-Goubault-Haucourt-Rausen 2016]

Consider a program with $n + 1$ processes and $(r_i)_{i \in [n]}$ rounds.

Protocol Complex [Herlihy-Kozlov-Rasjbaum 2013]

- **Vertex:** (process, local memory)
- **Maximal Simplex:** $\{(0, \ell_0), \dots, (n, \ell_n)\}$ where ℓ_i is the local view by process i of the global execution.

Examples



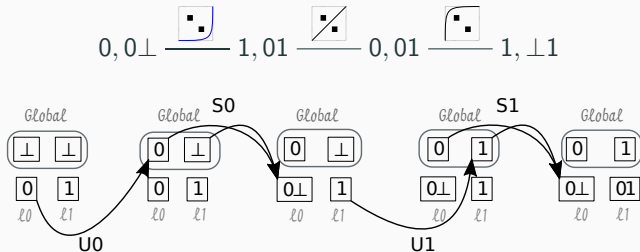
$U_1 S_1 U_0 S_0 U_2 S_2$

Consider a program with $n + 1$ processes and $(r_i)_{i \in [n]}$ rounds.

Protocol Complex [Herlihy-Kozlov-Rasjbaum 2013]

- **Vertex:** (process, local memory)
- **Maximal Simplex:** $\{(0, \ell_0), \dots, (n, \ell_n)\}$ where ℓ_i is the local view by process i of the global execution.

Examples

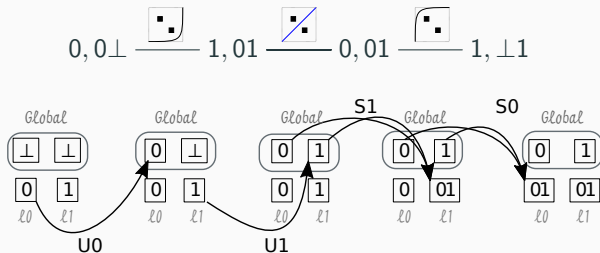


Consider a program with $n + 1$ processes and $(r_i)_{i \in [n]}$ rounds.

Protocol Complex [Herlihy-Kozlov-Rasjbaum 2013]

- **Vertex:** (process, local memory)
- **Maximal Simplex:** $\{(0, \ell_0), \dots, (n, \ell_n)\}$ where ℓ_i is the local view by process i of the global execution.

Examples



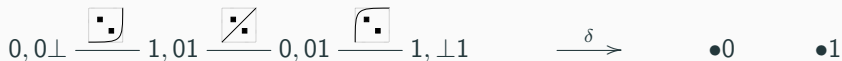
Impossibility Results

Theorem [Herlihy-Shavit 1999]

If the Protocol Complex is **contractible** then, the consensus is impossible.

Proof sketch

Assume there is an algorithm δ solving the task, for any execution.



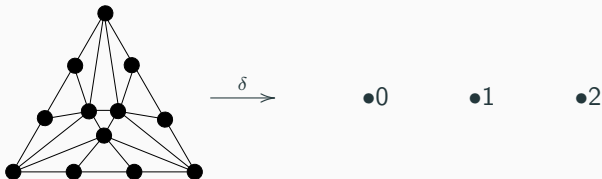
Impossibility Results

Theorem [Herlihy-Shavit 1999]

If the Protocol Complex is **contractible** then, the consensus is impossible.

Proof sketch

Assume there is an algorithm δ solving the task, for any execution.



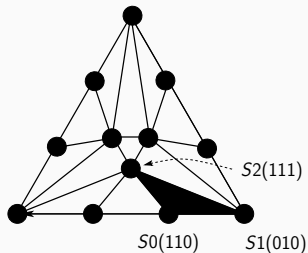
Geometrical Interpretation of Asynchronous Computability

Theorem (Goubault-Mimram-Tasson 2015)

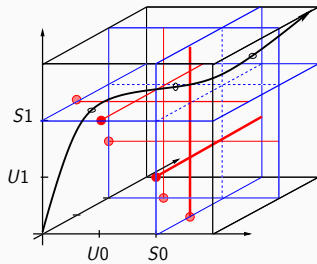
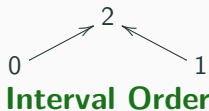
Equivalence between Simplexes, Interval Orders, Dipath, Traces.

$[U_1 U_0 S_1 S_0 U_2 S_2]$

Interleaving Trace \approx



Simplex



Dipath \rightsquigarrow

Contributions

- The **operational semantics** of execution traces
- The **equivalence** between two geometric semantics

Next steps

- Generalise this equivalence to other **communication primitives** and **failures**
- Use this equivalence to transfer properties from one model to the other

Perspectives

- Combine **differentiation** and **distributed** calculus
- Describe a denotational semantics of distributed systems

Table of contents

1. Differential λ -Calculus
2. Probabilistic Programming
3. Distributed Systems
4. Perspectives

Perspectives

Differential λ -calculus:

Contribution: A monad for mixed linear non linear variables.

Perspectives: Toward mixed substitution and theory of derivation.

Probabilistic Programming:

Contribution: Discrete and Continuous semantics.

Perspectives: Comparison with other models, Full Abstraction, Linear Logic, Recursive types,...

Distributed Computing:

Contribution: Equivalence between geometric semantics.

Perspectives: Generalise to different communication primitives and systematic method to produce protocol complexes

