

Models of Randomness

Part II: random types-as-closures

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Notation and concepts

SK = combinatory algebra

SKR = random extension ($R = \lambda x, y. x + y$)

(note $(x + y) + z \neq x + (y + z)$; really $\frac{x+y}{2}$)

SKJ = parallel/ambiguous extension ($J = \lambda x, y. x \mid y$)

(some authors write join $x \mid y$ instead $x \sqcup y$)

SKJR = random+ambiguous extension

All four assume HP-complete observational equivalence:

$M \sqsubseteq M'$ iff $\forall \underline{N}. M \underline{N} \text{ conv} \implies M' \underline{N} \text{ conv}$

where \underline{N} ranges over traces N_1, \dots, N_k of arguments.

Definable types-as-closures builds on 2007 talk,

<http://www.math.cmu.edu/~fho/notes/>

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look for "small" definable subspaces.

Abstract probability algebras

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$$x + x = x$$

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Compare with initial join-semilattice (“J-algebra”)

$$x \mid x = x$$

$$x \mid y = y \mid x$$

$$x \mid (y \mid x) = (x \mid y) \mid z$$

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How to sample, raising $\alpha \rightarrow \text{Rand } \beta$ to $\text{Rand } \alpha \rightarrow \text{Rand } \beta$?

Sampling booleans

Introduce $\mathbf{K} = \lambda x, y. x$, $\mathbf{F} = \lambda x, y. y$ with typing

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$$\text{sample}_{\text{bool}} = \lambda p, f. p \ (f \ \mathbf{K}) \ (f \ \mathbf{F})$$

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even coin toss

note the difference between

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deterministic

Sampling natural numbers

Let $\text{zero} = \lambda_.x.x$, $\text{succ} = \lambda n, f, x. f(n f x)$ with typing

$$\frac{}{\text{zero} : \text{nat}} \quad \frac{}{\text{succ} : \text{nat} \rightarrow \text{nat}} \quad \frac{n : \text{nat} \quad s : \alpha \rightarrow \alpha \quad z : \alpha}{n \ s \ z : \alpha}$$

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and sample with

$$\text{sample}_{\text{nat}} = \lambda p, f. p (f \circ \text{succ}) (f \ \text{zero})$$

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$$\text{sample}_{\text{nat}} = \lambda p, f. p (f \circ \text{succ}) (f \ \text{zero})$$

then lift $\text{succ} : \text{nat} \rightarrow \text{nat}$ to $\text{succ}' : \text{Rand nat} \rightarrow \text{Rand nat}$

$$\text{succ}' = \lambda p. \text{sample}_{\text{nat}} \ p \ \text{succ}$$

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Moral Church terms are already monadic

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...but first look at typing in lattice models.

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To minimize garbage, look for closures with small ranges.

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(see 2007 talk on definable closures for details)

A lattice with randomness

Seeking a random monad in a lattice model,
consider the free JR-algebra over SK, where
application right-distributes over both

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Call R-terms **mixtures**,

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so slurries can be infinitely deep.

JR-Bohm-trees

JR-Bohm trees are defined by

$$\frac{x \text{ var} \quad M_1, \dots, M_k \text{ BT}}{x M_1 \dots M_k \text{ BT}}$$

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Theorem

Every SKJR-term is equivalent to a slurry of BTs.

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Historical operational semantics for join is parallelism.

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For example...

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(recall we want small ranges, few inhabitants)

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Question What is the spectrum of dimensions?

Known At least $\{0, 1, 2^{\aleph_0}\}$.

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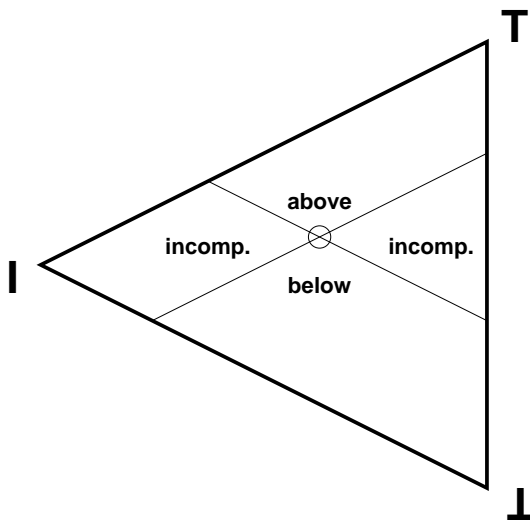
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Can we **disambiguate** to finite dimensional mixtures,
without determinizing? (unknown)

Mixtures of semiboleans

The space of \perp , \mathbf{I} , \top -mixtures is 2-dimensional:



Slurries of semibooleans

Theorem

\perp, \mathbf{I}, \top -slurries are completely characterized by their action on the unit interval $[\perp, \top]$.

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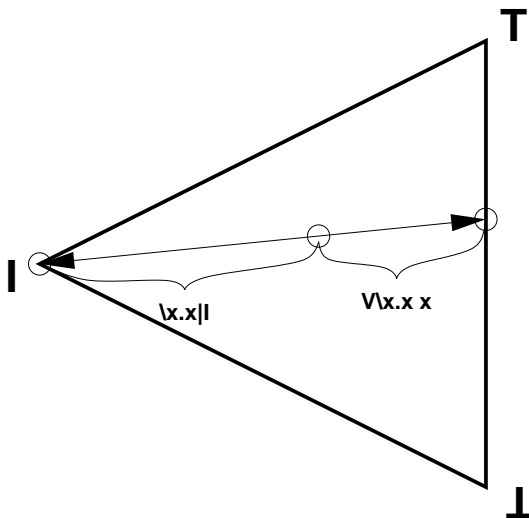
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Can we raise to a finite-dimensional subspace?

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The closure $\bigvee \lambda x.x$ is more useful
but has infinite dimensional range.

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Cumulative distribution functions yield a model:

Mixtures of booleans

In SKJ, $\text{inhab}(\text{bool}) = \{\perp, \mathbf{K}, \mathbf{F}, \mathbf{J} = \mathbf{K} \mid \mathbf{F}, \top\}$;
a “disambiguation” trick then raises \mathbf{J} to \top
yielding $\text{inhab}(\text{bool}) = \{\perp, \mathbf{K}, \mathbf{F}, \top\}$.

In SKJR, disambiguation interferes with randomness,
and we’re stuck with $\perp, \mathbf{K}, \mathbf{F}, \mathbf{J}, \top$ -mixtures.

$\perp, \mathbf{K}, \mathbf{F}, \mathbf{J}, \top$ -mixtures are 5-dimensional.

Cumulative distribution functions yield a model:

$$\{ (b, k, f, j, t) \in [0, 1]^5 \\ | k \geq b, f \geq b, j + b \geq k + f, t \geq j \}$$

partially ordered componentwise.

Slurries of booleans

Theorem

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but then requires sequentialization...