

A Denotational Semantics for Low-Level Probabilistic Programs with Nondeterminism

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Probabilistic Programs



Draw random **data** from distributions



Condition **control-flow** at random

Low-Level Probabilistic Programs

High-Level Features:

- Functional (Borgström et al. 2016)
- Higher-order (Ehrhard, Pagani, and Tasson 2018)
- Recursive types (Vákár, Kammar, and Staton 2019)

COMPILER
⇒

Low-Level Features:

- Imperative
- Unstructured control-flow

Operational semantics:

(Ferrer Fioriti and Hermanns 2015)

Denotational semantics:

This work

Formal semantics has been well studied.

Benefits of A Denotational Semantics

- Abstraction from details about program executions
- Compositionality

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The following code implements a variant of geometric distributions.

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n := 0;
while prob(0.9) do
  n := n + 1;
  if n ≥ 10 then break
  else continue
od
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There are multiple possible executions of the program, e.g., n could end up with 0, 3, or 10.

Principle

Probabilistic programs establish input/**output-distribution** relations. A probabilistic program can be modeled as a function in $X \rightarrow \mathcal{D}(X)$, where X is a program state space and $\mathcal{D}(X)$ consists of probability distributions over X .

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Nondeterminism

Sources

- Agents for Markov decisions processes (MDPs)
- Abstraction and refinement on programs

A Common Resolution

A nondeterministic function f from X to Y is a set-valued function that maps an input to a collection of outputs, i.e.,

$$f \in X \rightarrow \wp(Y).$$

Nondeterminism in Probabilistic Programming

A nondeterministic function f from X to $\mathcal{D}(X)$ should have the signature

$$f \in X \rightarrow \wp(\mathcal{D}(X)),$$

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When to Resolve Nondeterminism?

X is a program state space. $\mathcal{D}(X)$ consists of probability distributions over X .

The Common Resolution: Input **Prior to** Nondeterminism

$$f \in X \rightarrow \wp(\mathcal{D}(X))$$

What about: Nondeterminism **Prior to** Input?

$$f \in \wp(X \rightarrow \mathcal{D}(X))$$

Intuition: A nondeterministic program is a specification that models a **collection** of deterministic refinements.

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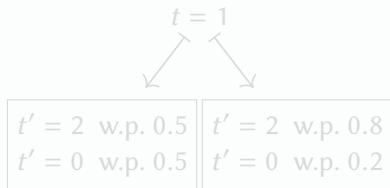
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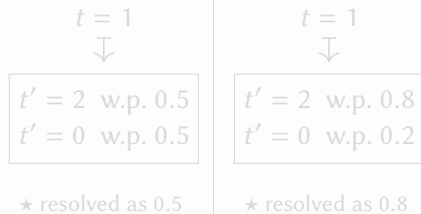
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\star resolved **after** t is given

Nondeterminism-First



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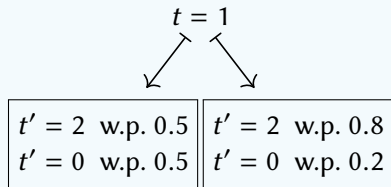
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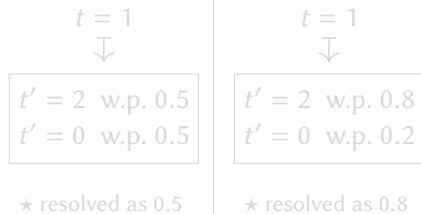
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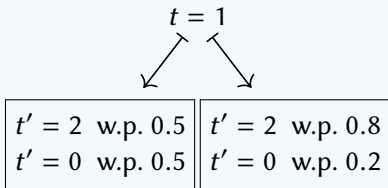
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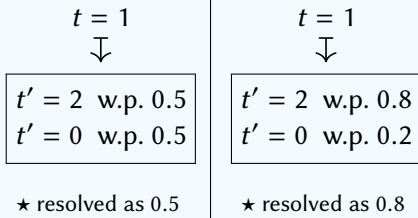
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Consider the following program P where \star represents nondeterminism.

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if prob( $\star$ ) then  $t := t + 1$  else  $t := t - 1$  fi
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Relational Reasoning about Refinements of a Program

- For all refinements P' of P , for all t_1, t_2 , can we prove that $\mathbb{E}_{t'_1 \sim P'(t_1), t'_2 \sim P'(t_2)}[t'_1 - t'_2] = t_1 - t_2$?
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Contributions

- We develop a denotational semantics for **low-level** probabilistic programs with unstructured control-flow, general recursion, and nondeterminism.
- We study different resolutions for nondeterminism and propose a new model that involves nondeterminacy among **state transformers**.
- We devise an **algebraic** framework for denotational semantics, which can be instantiated with different resolutions for nondeterminism.

Outline

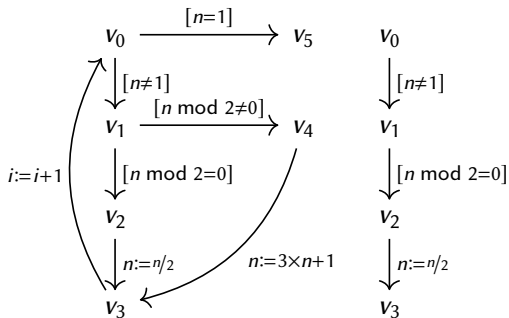
Motivation

Control-Flow Hyper-Graphs

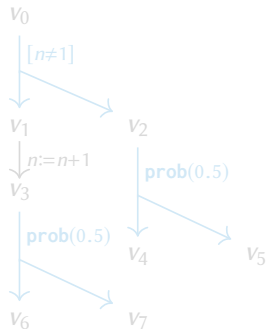
Algebraic Denotational Semantics

Nondeterminism-First

Representation of Low-Level Probabilistic Programs



A standard CFG and an execution path

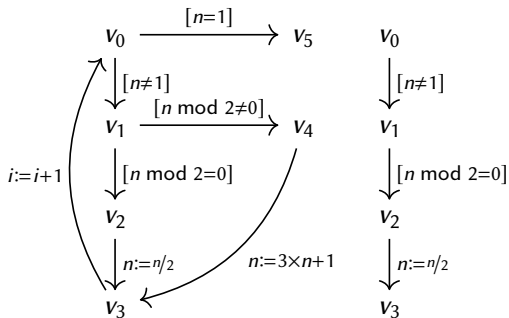


A tree-like **hyper-path**

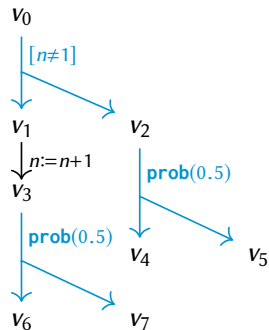
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For probabilistic programs, execution paths are **not independent**. A formal semantics should reason about **distributions** over paths.

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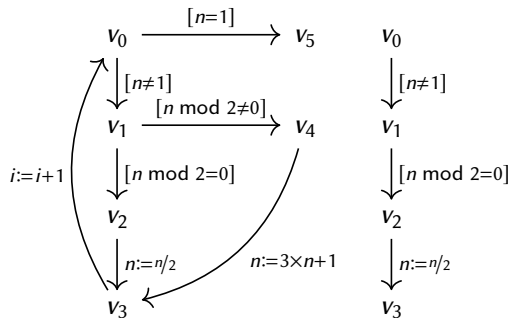


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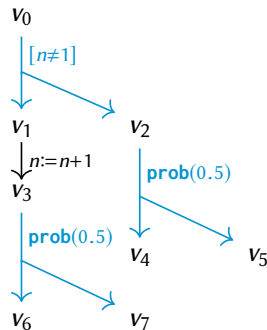
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Paths vs. Hyper-Paths

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if ★ then if prob(0.5) then t := 0 else t := 1 fi
           else if prob(0.8) then t := 0 else t := 1 fi fi
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Paths Annotated with Probabilities



Hyper-Paths, each of which stands for a **distribution**



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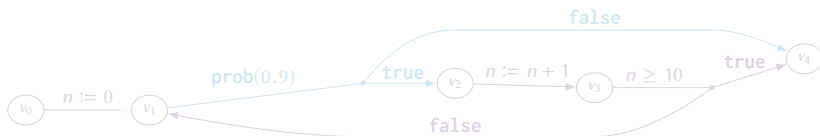


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Control-Flow Hyper-Graphs

- Hyper-graphs are directed graphs with **hyper-edges** that could have multiple destinations. **Hyper-paths** are made up of hyper-edges.
- The following hyper-graph

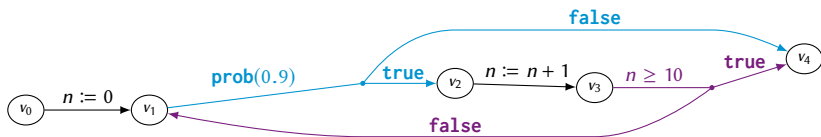


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Develop a denotational semantics that can be instantiated with different resolutions of nondeterminism.

An Algebraic Approach

- Perform reasoning in some **abstract** space of program states and state transformers.
- The state transformers should obey some algebraic **laws**.
- For example, the command **skip** should be interpreted as an **identity** element for sequencing in the algebra of transformers.

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The Algebra

Actions

skip

$x := x + 5$

$k \sim \text{Binomial}(10, 0.5)$

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SEMANTIC FUNCTION

State Transformers M

equipped with

sequencing \otimes

conditional-choice $\varphi \diamond$

nondeterministic-choice \cup

$$\langle M, \sqsubseteq, \otimes, \varphi \diamond, \cup, \perp, 1 \rangle$$

- $\langle M, \sqsubseteq \rangle$ forms a directed complete partial order (dcpo) with \perp as its least element.
- $\langle M, \otimes, 1 \rangle$ forms a monoid.
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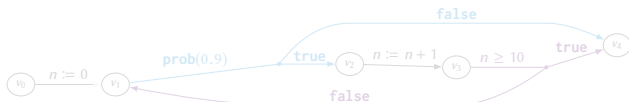
Fixpoint Semantics for Hyper-Graphs

Principle

The semantics of a node in the control-flow hyper-graph is a summary of computation that **continues from** that node.

Recall the control-flow hyper-graph below.

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n := 0;
while prob(0.9) do
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Semantics is defined as the **least** solution to the following equation system

$$\begin{aligned} S(v_0) &= \text{seq}[n := 0](S(v_1)) & S(v_2) &= \text{seq}[n := n + 1](S(v_3)) & S(v_4) &= 1 \\ S(v_1) &= \text{prob}[0.9](S(v_2), S(v_4)) & S(v_3) &= \text{cond}[n \geq 10](S(v_4), S(v_1)) \end{aligned}$$

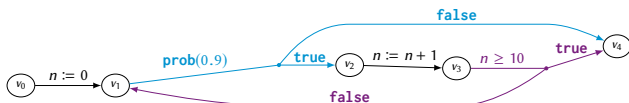
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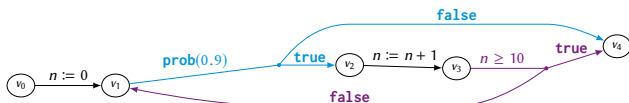
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A Denotational Semantics without Nondeterminism

- $X \stackrel{\text{def}}{=} \text{Var} \rightarrow_{\text{fin}} \mathbb{Q}$ and $M \stackrel{\text{def}}{=} X \rightarrow \underline{\mathcal{D}}(X)$.
- $\underline{\mathcal{D}}(X)$ stands for **sub-probability distributions** on X , i.e., $\Delta \in \underline{\mathcal{D}}(X)$ iff $\Delta : X \rightarrow [0, 1]$ and $\sum_{x \in X} \Delta(x) \leq 1$.
- For actions act , we have $\llbracket \text{act} \rrbracket \in M$.
- For conditions φ , we have $\llbracket \varphi \rrbracket : X \rightarrow [0, 1]$, e.g., $\llbracket \text{prob}(p) \rrbracket \stackrel{\text{def}}{=} \lambda_ . p$.
- $f \sqsubseteq g \stackrel{\text{def}}{=} \forall x \in X : \forall x' \in X : f(x)(x') \leq g(x)(x')$.
- $f \otimes g \stackrel{\text{def}}{=} \lambda x . \lambda x'' . \sum_{x' \in X} f(x, x') \cdot g(x', x'')$.
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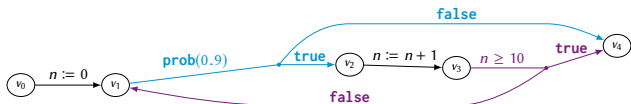
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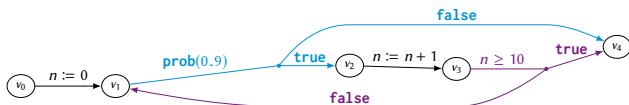
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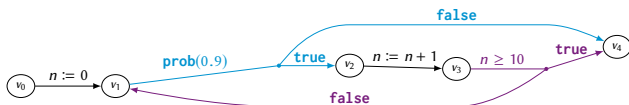
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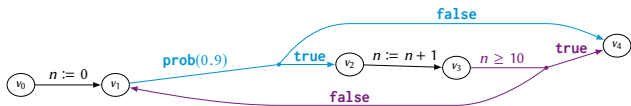
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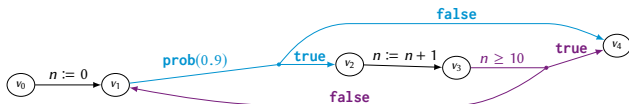
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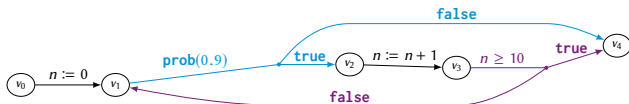
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Outline

Motivation

Control-Flow Hyper-Graphs

Algebraic Denotational Semantics

Nondeterminism-First

Sub-Probability Kernels

Definition

A function $\kappa : X \rightarrow \underline{\mathcal{D}}(X)$ is called a **sub-probability kernel**. The set of kernels is denoted by $\underline{\mathcal{K}}(X)$.

Goal

The common resolution for nondeterminism admits the following signature

$$X \rightarrow \wp(\underline{\mathcal{D}}(X)),$$

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Reasoning with Nondeterminism-First

Example

Recall the following nondeterministic program P

if $\text{prob}(\star)$ **then** $t := t + 1$ **else** $t := t - 1$ **fi**

Then the common resolution for nondeterminism derives

$$\lambda t. \{r \cdot \delta(t + 1) + (1 - r) \cdot \delta(t - 1) \mid r \in [0, 1]\},$$

but the nondeterminism-first model leads to

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With the new model, we can prove that for every refinement P' with \star resolved as $r \in [0, 1]$, for all t_1, t_2 , we have

$$\begin{aligned} \mathbb{E}_{t'_1 \sim P'(t_1), t'_2 \sim P'(t_2)}[t'_1 - t'_2] &= \mathbb{E}_{t'_1 \sim P'(t_1)}[t'_1] - \mathbb{E}_{t'_2 \sim P'(t_2)}[t'_2] \\ &= (r(t_1 + 1) + (1 - r)(t_1 - 1)) - (r(t_2 + 1) + (1 - r)(t_2 - 1)) \\ &= t_1 - t_2 \end{aligned}$$

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Necessary Conditions

We need to identify a subset \mathcal{A} of $\wp(\underline{\mathcal{K}}(X))$ as the collection of admissible semantic objects.

- \mathcal{A} admits a semilattice operation \cup (used as **nondeterministic-choice**), s.t. for all $A \in \mathcal{A}$, $A \cup A = A$.
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For all $A \in \mathcal{A}$, we have $A \cup A = A$, therefore we should also have $\forall \phi \in X \rightarrow [0, 1]: \forall \kappa_1, \kappa_2 \in A: \kappa_1 \phi \diamond \kappa_2 \in A$.

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Let $\phi \cdot \kappa \stackrel{\text{def}}{=} \lambda_X. \lambda_{X'}. \phi(x) \cdot \kappa(x)(x')$ and $\kappa_1 + \kappa_2 \stackrel{\text{def}}{=} \lambda_X. \lambda_{X'}. \kappa_1(x)(x') + \kappa_2(x)(x')$.
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A G-Convex Powerdomain for Nondeterminism-First

Idea

Construct a Plotkin-style powerdomain on $\underline{\mathcal{K}}(X)$, **except that g-convexity** replaces standard convexity in the development.

Example

Consider the following nondeterministic program P

if \star **then** $t := t + 1$ **else** $t := t - 1$ **fi**

Let the state space $X \stackrel{\text{def}}{=} \mathbb{Z}$ represent the value of t . The common resolution for nondeterminism gives the following semantics

$$\lambda t. \{r \cdot \delta(t+1) + (1-r) \cdot \delta(t-1) \mid r \in [0, 1]\},$$

while the nondeterminism-first resolution derives

$$\{\lambda t. \phi(t) \cdot \delta(t+1) + (1-\phi(t)) \cdot \delta(t-1) \mid \phi \in \mathbb{Z} \rightarrow [0, 1]\}.$$

A G-Convex Powerdomain for Nondeterminism-First

Idea

Construct a Plotkin-style powerdomain on $\underline{\mathcal{K}}(X)$, **except that g-convexity** replaces standard convexity in the development.

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This Work

We have developed an **algebraic** framework for denotational semantics of **low-level** probabilistic programs, which can be instantiated with different models of nondeterminism, including the common resolution for nondeterminism and the new **nondeterminism-first**.

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