

Running Probabilistic Programs Backward

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Abstract. To be useful in Bayesian practice, a probabilistic language must support conditioning: imposing constraints in a way that preserves the relative probabilities of program outputs. Every language to date that supports probabilistic conditioning also places seemingly artificial restrictions on legal programs, such as disallowing recursion and restricting conditions to simple equality constraints such as $x = 2$. We develop a semantics for a first-order language with recursion, probabilistic choice and conditioning. Distributions over program outputs are defined by the probabilities of their preimages, a measure-theoretic approach that ensures the language is not artificially limited. Preimages are generally uncomputable, so we derive an approximating semantics for computing rectangular covers of preimages. We implement the approximating semantics directly in Typed Racket and Haskell.

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1 Introduction

It is primarily Bayesian practice that drives probabilistic language development. To be useful, a probabilistic language must support **conditioning**, or imposing constraints in a way that preserves the relative probabilities of outputs.

Unfortunately, there is currently no efficient probabilistic language implementation that supports conditioning and places no extraneous restrictions on legal programs. Most commonly, languages that support conditioning disallow recursion, allow only discrete or continuous distributions, and restrict conditions to the form $x = c$.

These common language restrictions arise from reasoning about probability using **densities**, which are functions from random values to *changes* in probability. While simple and convenient, densities have many limitations. For example, densities for random values with different dimension are incomparable, and they cannot be defined on infinite products.

Densities generally cannot define distributions for the outputs of discontinuous functions. For example, suppose we want to model a thermometer that reports in the range $[0, 100]$, and that the temperature it would report (if it could) is distributed according to a bell curve. We might encode the process as

$$\begin{aligned} t' := & \text{let } t := \text{normal } \mu \ 1 \\ & \text{in } \max\ 0\ (\min\ 100\ t) \end{aligned} \tag{1}$$

While \mathbf{t} 's distribution has a density (a standard bell curve at mean μ), the distribution of \mathbf{t}' does not.

Densities do not allow reasoning about arbitrary conditions. If x and y are primitive random variables—loosely, untransformed probabilistic values, such as \mathbf{t} in (1)—then **Bayes' law for densities** gives the density of x given y :

$$f_x(x|y) = \frac{f_y(y|x) \cdot \pi_x(x)}{\int f_y(y|x) \cdot \pi_x(x) dx} \quad (2)$$

Bayesians interpret probabilistic processes as defining densities π_x and f_y , and use (2) to discover the density of x given $y = c$ for some constant c . While x given $\sin(y) = -1$ and x given $x + y = 0$ are perfectly sensible to reason about, Bayes' law for densities cannot express them. Thus, reasoning with densities disallows all but the simplest conditions.

1.1 Probability Measures

Measure-theoretic probability [14] is widely believed to be able to define every reasonable distribution that densities cannot. It mainly does this by *assigning probabilities to sets* instead of *assigning changes in probability to values*. Functions that do so are probability **measures**. In contrast to densities, probabilities of sets of values with different dimension *are* comparable, and probability measures *can* be defined on infinite products.

If a probability measure P assigns probabilities to subsets of X and $f : X \rightarrow Y$, then the **preimage measure**

$$\Pr[B] = P(f^{-1}(B)) \quad (3)$$

defines the distribution over Y , where $f^{-1}(B)$ is the subset of f 's domain X for which f yields a value in B . In the thermometer example (1), f would be an interpretation of the program as a function, X would be the set of all random sources, and Y would be \mathbb{R} . For any $B \subseteq Y$, $f^{-1}(B)$ is well-defined, regardless of discontinuities.

Measure-theoretic probability supports any kind of condition. The probability of $B' \subseteq Y$ given $B \subseteq Y$ is

$$\Pr[B' | B] = \Pr[B' \cap B] / \Pr[B] \quad (4)$$

if $\Pr[B] > 0$. If $\Pr[B] = 0$, conditional probabilities can be calculated by applying (4) to descending sequences $B_1 \supseteq B_2 \supseteq B_3 \supseteq \dots$ of positive-probability sets whose intersection is B , and taking a limit. If $Y = \mathbb{R} \times \mathbb{R}$, for example, the distribution over $\langle x, y \rangle \in Y$ given that $x + y = 0$ can be calculated using a descending sequence of sets defined by $B_n = \{\langle x, y \rangle \in Y \mid |x + y| < 2^{-n}\}$.

Unfortunately, there is a complicated technical restriction: only *measurable* subsets of X and Y can be assigned probabilities. This and having to take limits tend to drive practitioners to densities, even though they are so limited.

1.2 Measure-Theoretic Semantics

Because purely functional languages do not allow side effects (except usually nontermination), programmers must write probabilistic programs as functions from a random source to outputs. Monads and other categorical classes such as idioms (i.e. applicative functors) can make doing so easier [10, 25].

It seems this approach should make it easy to interpret probabilistic programs measure-theoretically. For a probabilistic program $f : X \rightarrow Y$, the probability measure on output sets $B \subseteq Y$ should be defined by preimages of B under f and the probability measure on X . Unfortunately, it is difficult to turn this simple-sounding idea into a compositional semantics, for the following reasons.

1. Preimages can be defined only for functions with observable domains, which excludes lambdas.
2. If subsets of X and Y must be measurable, taking preimages under f must preserve measurability (we say f itself is measurable). Proving the conditions under which this is true is difficult, especially if f may not terminate.
3. It is very difficult to define probability measures for arbitrary spaces of measurable functions [3].

Implementing a language based on such a semantics is complicated because

4. Contemporary mathematics is unlike any implementation's host language.
5. It requires running Turing-equivalent programs backward, efficiently, on possibly uncountable sets of outputs.

We address 1 and 4 by developing our semantics in λ_{ZFC} [26], a λ -calculus with infinite sets, and both extensional and intensional functions. We address 5 by deriving and implementing a *conservative approximation* of the semantics.

XXX: something about difficulty 2

For difficulty 3, we have discovered that the “first-orderness” of arrows [9] is a perfect fit for the “first-orderness” of measure theory.

1.3 Arrow Solution Overview

Using arrows, we define an *exact* semantics and an *approximating* semantics. Our exact semantics consists of

- A semantic function which, like the arrow calculus [17] semantic function, transforms first-order programs into the computations of an arbitrary arrow.
- Arrows for evaluating expressions in different ways.

This commutative diagram describes the relationships among the arrows used to define the exact semantics:

$$\begin{array}{ccc}
 X \rightsquigarrow_{\perp} Y & \xrightarrow{\text{lift}_{\text{pre}}} & X \rightsquigarrow_{\text{pre}} Y \\
 \eta_{\perp^*} \downarrow & & \downarrow \eta_{\text{pre}^*} \\
 X \rightsquigarrow_{\perp^*} Y & \xrightarrow{\text{lift}_{\text{pre}^*}} & X \rightsquigarrow_{\text{pre}^*} Y
 \end{array} \tag{5}$$

In the top row, $X \rightsquigarrow_{\perp} Y$ computations are functions that may raise errors and $X \rightsquigarrow_{\text{pre}} Y$ computations compute preimages. The computations of the arrows in the bottom row are like those in the top, except they thread an infinite store of random values, and always terminate. (We can do this because in λ_{ZFC} , Turing-uncomputable programs are definable.) Most of our correctness theorems rely on proofs that every morphism in (5) is a homomorphism.

Our approximating semantics consists of the same semantic function and an arrow $X \rightsquigarrow_{\text{pre}^*}' Y$, derived from $X \rightsquigarrow_{\text{pre}} Y$, for computing conservative approximations of preimages. An implementation is comprised of the semantic function, and the $X \rightsquigarrow_{\perp} Y$ and $X \rightsquigarrow_{\text{pre}^*}' Y$ arrows' combinators.

2 Operational Metalanguage

We write programs in λ_{ZFC} [26], an untyped, call-by-value λ -calculus designed for deriving implementable programs from contemporary mathematics.

Contemporary mathematics—measure theory in particular—is usually done in **ZFC: Zermelo-Fraenkel** set theory with the axiom of **Choice**. ZFC has only first-order functions and no general recursion, which makes implementing a language defined by a transformation into ZFC quite difficult. The problem is exacerbated if implementing the language requires approximation. Targeting λ_{ZFC} instead allows creating an exact semantics and deriving an approximating semantics without changing languages.

In λ_{ZFC} , essentially every set is a value, as well as every lambda and every set of lambdas. All operations, including operations on infinite sets, are assumed to complete instantly if they terminate.

Almost everything definable in ZFC can be defined by a finite λ_{ZFC} program. Essentially every ZFC theorem applies to λ_{ZFC} 's set values without alteration. Further, proofs about λ_{ZFC} 's set values apply directly to ZFC sets, assuming the existence of an inaccessible cardinal.¹

In λ_{ZFC} , algebraic data structures are encoded as sets; e.g. the pair $\langle x, y \rangle$ can be encoded as $\{\{x\}, \{x, y\}\}$. Only the *existence* of encodings into sets is important, as it means data structures inherit a defining characteristic of sets: strictness. More precisely, the lengths of paths to data structure leaves is unbounded, but each path must be finite. Less precisely, data may be “infinitely wide” (such as \mathbb{R}) but not “infinitely tall” (such as infinite trees and lists).

λ_{ZFC} is untyped so its users can define an auxiliary type system that best suits their application area. For this work, we use a manually checked, polymorphic type system characterized by these rules:

- A free type variable is universally quantified; if uppercase, it denotes a set.
- A set denotes a member of that set.
- $x \Rightarrow y$ denotes a partial function.
- $\langle x, y \rangle$ denotes a pair of values with types x and y .
- **Set** x denotes a set with members of type x .

¹ A mild assumption, as $\text{ZFC} + \kappa$ is a smaller theory than Coq's [4].

Because the type $\text{Set } X$ denotes the same values as the set $\mathcal{P} X$ (i.e. subsets of the set X) we regard them as equivalent. Similarly, $\langle X, Y \rangle$ is equivalent to $X \times Y$.

We write λ_{ZFC} programs in heavily sugared λ -calculus syntax, with an `if` expression and additional primitives such as membership $(\in) : x \Rightarrow \text{Set } x \Rightarrow \text{Bool}$, powerset $\mathcal{P} : \text{Set } x \Rightarrow \text{Set } (\text{Set } x)$ and big union $\bigcup : \text{Set } (\text{Set } x) \Rightarrow \text{Set } x$. We use binding forms such as indexed unions $\bigcup_{x \in e_A} e$, destructuring binds as in `swap` $\langle x, y \rangle := \langle y, x \rangle$, and comprehensions like $\{x \in A \mid x \in B\}$. We assume we have logical operators, bounded quantifiers, and typical set operations.

In set theory, because functions are encoded as sets of input-output pairs, they inherit the extensionality of sets. The increment function for the natural numbers, for example, is $\{\langle 0, 1 \rangle, \langle 1, 2 \rangle, \langle 2, 3 \rangle, \dots\}$. We call these **mappings** and intensional functions **lambdas**, and use **function** to mean either. For convenience, as with lambdas, we use adjacency (e.g. $(f \ x)$) to apply mappings.

The set $X \rightarrow Y$ contains all the *total* mappings from X to Y . We use total mappings as possibly infinite vectors, with application for indexing. Indexing functions are produced by

$$\begin{aligned} \pi : J &\Rightarrow (J \rightarrow X) \Rightarrow X \\ \pi \ j \ f &:= f \ j \end{aligned} \tag{6}$$

which is particularly useful when f is unnamed.

Because of the way λ_{ZFC} 's lambda terms are defined, for two lambdas e_1 and e_2 , $e_1 = e_2$ reduces to `true` when e_1 and e_2 are alpha-equivalent. For example, $(\lambda a. a) = (\lambda b. b)$ reduces to `true`, but $(\lambda a. 2) = (\lambda a. 1 + 1)$ reduces to `false`.

Any λ_{ZFC} term e used as a truth statement means “ e reduces to `true`.” Therefore, the terms $(\lambda a. a) \ 1$ and 1 are (externally) unequal, but $(\lambda a. a) \ 1 = 1$.

Any truth statement e implies e terminates. In particular, $e_1 = e_2$ implies e_1 and e_2 both terminate. However, we often want to say that e_1 and e_2 are equivalent when they both loop.

Definition 1 (observational equivalence). *Two λ_{ZFC} terms e_1 and e_2 are **observationally equivalent**, written $e_1 \equiv e_2$, when $e_1 = e_2$ or both e_1 and e_2 do not terminate.*

It might seem helpful to introduce even coarser notions of equivalence, such as applicative bisimilarity [2]. However, we do not want internal equality and external equivalence to differ too much, and we want the flexibility of extending “ \equiv ” with type-specific rules.

To save space, we elide complex proofs and give sketches for simple ones.

3 Arrows and First-Order Semantics

Like monads [27] and idioms [19], arrows [9] are used to thread effects through computations in a way that imposes structure on the computations. Unlike monad and idiom computations, arrow computations are always

- Function-like: An arrow computation of type $x \rightsquigarrow y$ must behave like a corresponding function of type $x \Rightarrow y$ (in a sense we explain shortly).
- First-order: There is no way to derive a computation $\mathbf{app} : \langle x \rightsquigarrow y, x \rangle \rightsquigarrow y$ from an arrow’s minimal definition.

The first property makes arrows a perfect fit for a compositional translation from expressions to functions, or to computations that compute preimages under those same functions. The second property makes arrows a perfect fit for a measure-theoretic semantics in particular, as **app** in the function arrow is generally not measurable [3]. Targeting arrows in the semantics therefore gives some assurance that we can meet measure theory’s requirement that preimage measure be defined only for measurable functions.

3.1 Alternative Arrow Definitions and Laws

To make applying measure-theoretic theorems easier, and to simplify interpreting let-calculus expressions as arrow computations, we do not give typical minimal arrow definitions. For each arrow **a**, instead of \mathbf{first}_a , we define $(\&\&\&_a)$ —typically called **fanout**, but its use will be clearer if we call it **pairing**—which applies two functions to an input and returns the pair of their outputs. One way to strengthen an arrow **a** is to define an additional combinator \mathbf{left}_a , which can be used to choose an arrow computation based on the result of another. Again, we define a different combinator, \mathbf{ifte}_a (“if-then-else”).

In a nonstrict λ -calculus, defining a choice combinator allows writing recursive functions using nothing but arrow combinators and lifted, pure functions. However, a strict λ -calculus needs an extra combinator to defer computations in conditional branches. For example, define the **function arrow** with choice:

$$\begin{aligned} \mathbf{arr} \ f &:= f \\ (f_1 \ggg f_2) \ a &:= f_2 (f_1 \ a) \\ (f_1 \&\&\& f_2) \ a &:= \langle f_1 \ a, f_2 \ a \rangle \\ \mathbf{ifte} \ f_1 \ f_2 \ f_3 \ a &:= \text{if } (f_1 \ a) \ (f_2 \ a) \ (f_3 \ a) \end{aligned} \tag{7}$$

and try to define the following recursive function:

$$\mathbf{halt-on-true} := \mathbf{ifte} (\mathbf{arr} \ \mathbf{id}) (\mathbf{arr} \ \mathbf{id}) \ \mathbf{halt-on-true} \tag{8}$$

The defining expression loops in a strict λ -calculus. In a nonstrict λ -calculus, it loops only when applied to **false**. Using $\mathbf{lazy} \ f \ a := f \ 0 \ a$, which receives thunks and returns arrow computations, we can write **halt-on-true** using $\mathbf{lazy} \ \lambda 0. \mathbf{halt-on-true}$ for the else branch, so that it loops only when applied to **false** in any λ -calculus.

Definition 2 (arrow with choice). A binary type constructor (\rightsquigarrow_a) and

$$\begin{aligned} \mathbf{arr}_a &: (x \Rightarrow y) \Rightarrow (x \rightsquigarrow_a y) \\ (\ggg_a) &: (x \rightsquigarrow_a y) \Rightarrow (y \rightsquigarrow_a z) \Rightarrow (x \rightsquigarrow_a z) \\ (\&\&\&_a) &: (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_a z) \Rightarrow (x \rightsquigarrow_a \langle y, z \rangle) \end{aligned} \tag{9}$$

define an **arrow** if certain monoid, homomorphism, and structural laws hold. The additional combinators

$$\begin{aligned} \text{ifte}_a : (x \rightsquigarrow_a \text{Bool}) &\Rightarrow (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_a y) \\ \text{lazy}_a : (1 \Rightarrow (x \rightsquigarrow_a y)) &\Rightarrow (x \rightsquigarrow_a y) \end{aligned} \quad (10)$$

where $1 = \{0\}$, define an **arrow with choice** if certain additional homomorphism and structural laws hold.

All of our arrows are arrows with choice, so we simply call them arrows.

The necessary homomorphism laws can be put in terms of more general homomorphism properties that deal with distributing an arrow-to-arrow lift, which we use extensively to prove correctness.

Definition 3 (arrow homomorphism). A function $\text{lift}_b : (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_b y)$ is an **arrow homomorphism** from arrow a to arrow b if the following distributive laws hold for appropriately typed f , f_1 , f_2 and f_3 :

$$\text{lift}_b (\text{arr}_a f) \equiv \text{arr}_b f \quad (11)$$

$$\text{lift}_b (f_1 \ggg_a f_2) \equiv (\text{lift}_b f_1) \ggg_b (\text{lift}_b f_2) \quad (12)$$

$$\text{lift}_b (f_1 \&\&_a f_2) \equiv (\text{lift}_b f_1) \&\&_b (\text{lift}_b f_2) \quad (13)$$

$$\text{lift}_b (\text{ifte}_a f_1 f_2 f_3) \equiv \text{ifte}_b (\text{lift}_b f_1) (\text{lift}_b f_2) (\text{lift}_b f_3) \quad (14)$$

$$\text{lift}_b (\text{lazy}_a f) \equiv \text{lazy}_b \lambda 0. \text{lift}_b (f \ 0) \quad (15)$$

The arrow homomorphism laws state that $\text{arr}_a : (x \Rightarrow y) \Rightarrow (x \rightsquigarrow_a y)$ must be a homomorphism from the function arrow (7) to arrow a . Roughly, arrow computations that do not use additional combinators can be transformed into arr_a applied to a pure computation. They must be *function-like*.

Rather than prove each necessary arrow law, we prove arrows are *epimorphic* (not necessarily *isomorphic*) to arrows for which the laws are known to hold.

Definition 4 (arrow epimorphism). An arrow homomorphism $\text{lift}_b : (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_b y)$ that has a right inverse is an **arrow epimorphism** from a to b .

Theorem 1. If $\text{lift}_b : (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_b y)$ is an arrow epimorphism and the combinators of a define an arrow, then the combinators of b define an arrow.

Proof. For each law, substitute right inverses, factor out lift_b , apply law for arrow a , distribute lift_b , and cancel right inverses. \square

3.2 First-Order Let-Calculus Semantics

Fig. 1 defines a transformation $\llbracket \cdot \rrbracket_a$ from a first-order let-calculus to arrow computations for any arrow a .

A program is a sequence of definition statements followed by a final expression. The semantic function $\llbracket \cdot \rrbracket_a$ transforms each defining expression and the

$$\begin{aligned}
p &::= x := e; \dots; e \\
e &::= x \mid e \mid \text{let } e \mid \text{env } n \mid \langle e, e \rangle \mid \text{fst } e \mid \text{snd } e \mid \text{if } e \mid e \mid v \\
v &::= [\text{first-order constants}] \\
[x := e; \dots; e_{\text{body}}]_a &::= x := [e]_a; \dots; [e_{\text{body}}]_a \\
[x \mid e]_a &::= [\langle e, \rangle]_a \ggg_a x \\
[\langle e_1, e_2 \rangle]_a &::= [e_1]_a \&\&_a [e_2]_a \\
[\text{fst } e]_a &::= [e]_a \ggg_a \text{arr}_a \text{fst} \\
[\text{snd } e]_a &::= [e]_a \ggg_a \text{arr}_a \text{snd} \\
[v]_a &::= \text{arr}_a (\text{const } v) \\
\text{id} &::= \lambda a. a \\
\text{const } b &::= \lambda a. b
\end{aligned}$$

Fig. 1: Transformation from a let-calculus with first-order definitions and De-Bruijn-indexed bindings to computations in arrow **a**.

final expression into arrow computations. Functions are named, but local variables and arguments are not. Instead, variables are referred to by De Bruijn indexes, with 0 referring to the innermost binding.

Perhaps unsurprisingly, the interpretation acts like a stack machine. The final expression has type $\langle \rangle \rightsquigarrow_a y$, where y is the type of the program’s value, and $\langle \rangle$ denotes an empty list. Let-bindings push values onto the stack. First-order functions have type $\langle x, \langle \rangle \rangle \rightsquigarrow_a y$ where x is the argument type and y is the return type. Application sends a stack containing just an x .

We generally regard programs as if they were their final expressions. Thus, the following definition applies to both programs and expressions.

Definition 5 (well-defined expression). *An expression e is well-defined under arrow \mathbf{a} if $\llbracket e \rrbracket_{\mathbf{a}} : \mathbf{x} \rightsquigarrow_{\mathbf{a}} \mathbf{y}$ for some \mathbf{x} and \mathbf{y} , and $\llbracket e \rrbracket_{\mathbf{a}}$ terminates.*

From here on, we assume all expressions are well-defined. (The arrow \mathbf{a} will be clear from context.) This does not guarantee that *running* any given interpretation terminates; it just simplifies unqualified statements about expressions.

Most of our semantic correctness results rely on the following theorem.

Theorem 2 (homomorphisms distribute over expressions). *Let $\text{lift}_b : (\times \rightsquigarrow_a y) \Rightarrow (\times \rightsquigarrow_b y)$ be an arrow homomorphism. For all e , $\llbracket e \rrbracket_b \equiv \text{lift}_b \llbracket e \rrbracket_a$.*

Proof. By structural induction and homomorphism properties (11)–(15). \square

If we assume that lift_b defines correct behavior for arrow b in terms of arrow a , and prove that lift_b is a homomorphism, then by Theorem 2, $[\llbracket \cdot \rrbracket]_b$ is correct.

$X \rightsquigarrow_{\perp} Y ::= X \Rightarrow Y_{\perp}$	$\text{ifte}_{\perp} : (X \rightsquigarrow_{\perp} \text{Bool}) \Rightarrow (X \rightsquigarrow_{\perp} Y) \Rightarrow (X \rightsquigarrow_{\perp} Y) \Rightarrow (X \rightsquigarrow_{\perp} Y)$
$\text{arr}_{\perp} : (X \Rightarrow Y) \Rightarrow (X \rightsquigarrow_{\perp} Y)$	$\text{ifte}_{\perp} f_1 f_2 f_3 a :=$
$\text{arr}_{\perp} f := f$	$\text{case } f_1 a$
$(\ggg_{\perp}) : (X \rightsquigarrow_{\perp} Y) \Rightarrow (Y \rightsquigarrow_{\perp} Z) \Rightarrow (X \rightsquigarrow_{\perp} Z)$	$\text{true} \rightarrow f_2 a$
$(f_1 \ggg_{\perp} f_2) a := \text{if } (f_1 a = \perp) \perp (f_2 (f_1 a))$	$\text{false} \rightarrow f_3 a$
	$\perp \rightarrow \perp$
$(\&\&\&_{\perp}) : (X \rightsquigarrow_{\perp} Y_1) \Rightarrow (X \rightsquigarrow_{\perp} Y_2) \Rightarrow (X \rightsquigarrow_{\perp} \langle Y_1, Y_2 \rangle)$	$\text{lazy}_{\perp} : (1 \Rightarrow (X \rightsquigarrow_{\perp} Y)) \Rightarrow (X \rightsquigarrow_{\perp} Y)$
$(f_1 \&\&\&_{\perp} f_2) a := \text{if } (f_1 a = \perp \text{ or } f_2 a = \perp) \perp \langle f_1 a, f_2 a \rangle$	$\text{lazy}_{\perp} f a := f \ 0 \ a$

Fig. 2: Bottom arrow definitions.

4 The Bottom and Preimage Arrows

To use Theorem 2 to prove correct the interpretations of expressions as preimage arrow computations, we need the preimage arrow to be homomorphic to a simpler arrow whose behavior is well-understood. One obvious candidate is the function arrow (7). However, we will need to explicitly handle nontermination as an error value, so we need a slightly more complicated arrow for which running computations may raise an error.

Fig. 2 defines the **bottom arrow**. Its computations are of type $X \rightsquigarrow_{\perp} Y ::= X \Rightarrow Y_{\perp}$, where $Y_{\perp} ::= Y \cup \{\perp\}$ and \perp is an error value.

If we wish to claim that $X \rightsquigarrow_{\perp} Y$ computations obey the arrow laws, we need a notion of equivalence that is slightly coarser than observational equivalence.

Definition 6 (bottom arrow equivalence). *Two computations $f_1 : X \rightsquigarrow_{\perp} Y$ and $f_2 : X \rightsquigarrow_{\perp} Y$ are equivalent, or $f_1 \equiv f_2$, when $f_1 a \equiv f_2 a$ for all $a \in X$.*

It is not hard to show that the bottom arrow is epimorphic to the Maybe monad's Kleisli arrow; by Theorem 1, the arrow laws hold.

4.1 Lazy Preimage Mappings

To compute with infinite sets in the language implementation, we need an abstraction that makes it easy to replace computation on concrete sets with computation on abstract sets. Therefore, in the preimage arrow, we confine set computations to instances of

$$X \xrightarrow{\text{pre}} Y ::= \langle \text{Set } Y, \text{Set } Y \Rightarrow \text{Set } X \rangle \quad (16)$$

Like a mapping, an $X \xrightarrow{\text{pre}} Y$ has an observable domain—but computing the input-output pairs is delayed. We therefore call these **lazy preimage mappings**. The lack of \perp in the type makes ignore nonterminating inputs easier further on.

$X \xrightarrow{\text{pre}} Y ::= \langle \text{Set } Y, \text{Set } Y \Rightarrow \text{Set } X \rangle$	$\langle \cdot, \cdot \rangle_{\text{pre}} : (X \xrightarrow{\text{pre}} Y_1) \Rightarrow (X \xrightarrow{\text{pre}} Y_2) \Rightarrow (X \xrightarrow{\text{pre}} Y_1 \times Y_2)$
$\text{pre} : (X \rightsquigarrow_{\perp} Y) \Rightarrow (X \xrightarrow{\text{pre}} Y)$	$\langle \langle Y'_1, p_1 \rangle, \langle Y'_2, p_2 \rangle \rangle_{\text{pre}} :=$
$\text{pre } f \ A :=$ $\langle \text{image}_{\perp} f \ A, \lambda B. \text{preimage}_{\perp} f \ A \ B \rangle$	$\text{let } Y' := Y'_1 \times Y'_2$ $p := \lambda B. \bigcup_{(b_1, b_2) \in B} (p_1 \{b_1\}) \cap (p_2 \{b_2\})$ $\text{in } \langle Y', p \rangle$
$\emptyset_{\text{pre}} := \langle \emptyset, \lambda B. \emptyset \rangle$	$(\circ_{\text{pre}}) : (Y \xrightarrow{\text{pre}} Z) \Rightarrow (X \xrightarrow{\text{pre}} Y) \Rightarrow (X \xrightarrow{\text{pre}} Z)$
$\text{ap}_{\text{pre}} : (X \xrightarrow{\text{pre}} Y) \Rightarrow \text{Set } Y \Rightarrow \text{Set } X$	$\langle Z', p_2 \rangle \circ_{\text{pre}} h_1 := \langle Z', \lambda C. \text{ap}_{\text{pre}} h_1 (p_2 \ C) \rangle$
$\text{ap}_{\text{pre}} \langle Y', p \rangle \ B := p \ (B \cap Y')$	$(\uplus_{\text{pre}}) : (X \xrightarrow{\text{pre}} Y) \Rightarrow (X \xrightarrow{\text{pre}} Y) \Rightarrow (X \xrightarrow{\text{pre}} Y)$
$\text{range}_{\text{pre}} : (X \xrightarrow{\text{pre}} Y) \Rightarrow \text{Set } Y$	$h_1 \uplus_{\text{pre}} h_2 := \text{let } Y' := (\text{range}_{\text{pre}} h_1) \cup (\text{range}_{\text{pre}} h_2)$ $p := \lambda B. (\text{ap}_{\text{pre}} h_1 \ B) \cup (\text{ap}_{\text{pre}} h_2 \ B)$ $\text{in } \langle Y', p \rangle$
$\text{range}_{\text{pre}} \langle Y', p \rangle := Y'$	
$\text{image}_{\perp} : (X \rightsquigarrow_{\perp} Y) \Rightarrow \text{Set } X \Rightarrow \text{Set } Y$	$\text{preimage}_{\perp} : (X \rightsquigarrow_{\perp} Y) \Rightarrow \text{Set } X \Rightarrow \text{Set } Y \Rightarrow \text{Set } X$
$\text{image}_{\perp} f \ A := (\text{image } f \ A) \setminus \{\perp\}$	$\text{preimage}_{\perp} f \ A \ B := \{a \in A \mid f \ a \in B\}$

Fig. 3: Lazy preimage mappings and operations.

Converting a bottom arrow computation to a lazy preimage mapping requires computing its range, and constructing a delayed preimage computation:

$$\begin{aligned} \text{pre} : (X \rightsquigarrow_{\perp} Y) &\Rightarrow \text{Set } X \Rightarrow (X \xrightarrow{\text{pre}} Y) \\ \text{pre } f \ A &:= \langle \text{image}_{\perp} f \ A, \lambda B. \text{preimage}_{\perp} f \ A \ B \rangle \end{aligned} \quad (17)$$

Fig. 3 defines image_{\perp} , preimage_{\perp} , and further operations on preimage mappings. One is ap_{pre} , which applies a preimage mapping to any subset of its codomain, in a way that ensures using pre and ap_{pre} to compute preimages is the same as computing them using preimage_{\perp} .

Theorem 3 (ap_{pre} computes preimages). *Let $f : X \rightsquigarrow_{\perp} Y$. For all $A \subseteq X$ and $B \subseteq Y$, $\text{ap}_{\text{pre}} (\text{pre } f \ A) \ B \equiv \text{preimage}_{\perp} f \ A \ B$.*

Proof. Expand definitions; use basic facts about (\setminus) , (\cap) and image . \square

Other operations are $\langle \cdot, \cdot \rangle_{\text{pre}}$, which returns preimage mappings for computing preimages under pairing functions, and (\circ_{pre}) and (\uplus_{pre}) , which do the same for compositions and disjoint unions.

4.2 The Preimage Arrow

Now we can define an arrow that computes preimages of output sets.

Its computations should produce preimage mappings or be preimage mappings. However, we cannot have the latter (i.e. $X \rightsquigarrow_{\text{pre}} Y ::= X \xrightarrow{\text{pre}} Y$): we run into

$$\begin{array}{ll}
X \rightsquigarrow_{\text{pre}} Y ::= \text{Set } X \Rightarrow (X \xrightarrow{\text{pre}} Y) & \text{ifte}_{\text{pre}} : (X \rightsquigarrow_{\text{pre}} \text{Bool}) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y) \Rightarrow \\
& (X \rightsquigarrow_{\text{pre}} Y) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y) \\
\text{arr}_{\text{pre}} : (X \Rightarrow Y) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y) & \text{ifte}_{\text{pre}} h_1 h_2 h_3 A := \\
\text{arr}_{\text{pre}} := \text{lift}_{\text{pre}} \circ \text{arr}_{\perp} & \text{let } h'_1 := h_1 A \\
& h'_2 := h_2 (\text{ap}_{\text{pre}} h'_1 \{\text{true}\}) \\
& h'_3 := h_3 (\text{ap}_{\text{pre}} h'_1 \{\text{false}\}) \\
& \text{in } h'_2 \sqcup_{\text{pre}} h'_3 \\
(\ggg_{\text{pre}}) : (X \rightsquigarrow_{\text{pre}} Y) \Rightarrow (Y \rightsquigarrow_{\text{pre}} Z) \Rightarrow (X \rightsquigarrow_{\text{pre}} Z) & \text{lazy}_{\text{pre}} : (1 \Rightarrow (X \rightsquigarrow_{\text{pre}} Y)) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y) \\
(h_1 \ggg_{\text{pre}} h_2) A := \text{let } h'_1 := h_1 A & \text{lazy}_{\text{pre}} h A := \text{if } (A = \emptyset) \emptyset_{\text{pre}} (h \circ A) \\
& h'_2 := h_2 (\text{range}_{\text{pre}} h'_1) \\
& \text{in } h'_2 \circ_{\text{pre}} h'_1 \\
(\lll_{\text{pre}}) : (X \rightsquigarrow_{\text{pre}} Y) \Rightarrow (X \rightsquigarrow_{\text{pre}} Z) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y \times Z) & \text{lift}_{\text{pre}} := \text{pre} \\
(h_1 \lll_{\text{pre}} h_2) A := \langle h_1 A, h_2 A \rangle_{\text{pre}} &
\end{array}$$

Fig. 4: Preimage arrow definitions.

trouble trying to define arr_{pre} because a preimage mapping needs an observable range. Fortunately, if we define the *preimage arrow* type constructor as

$$X \rightsquigarrow_{\text{pre}} Y ::= \text{Set } X \Rightarrow (X \xrightarrow{\text{pre}} Y) \quad (18)$$

then we already have a lift $\text{lift}_{\text{pre}} : (X \rightsquigarrow_{\perp} Y) \Rightarrow (X \rightsquigarrow_{\text{pre}} Y)$ from the bottom arrow to the preimage arrow: **pre**. By Theorem 3, lifted bottom arrow computations compute correct preimages, exactly as we should expect them to.

Fig. 4 defines the preimage arrow. If the arrow combinator definitions make lift_{pre} a homomorphism, then $\llbracket \cdot \rrbracket_{\text{pre}}$ is correct. For this to be true, we need preimage arrow computations to be equivalent when they compute the same preimages.

Definition 7 (preimage arrow equivalence). *Two preimage arrow computations $h_1 : X \rightsquigarrow_{\text{pre}} Y$ and $h_2 : X \rightsquigarrow_{\text{pre}} Y$ are equivalent, or $h_1 \equiv h_2$, when $\text{ap}_{\text{pre}} (h_1 A) B \equiv \text{ap}_{\text{pre}} (h_2 A) B$ for all $A \subseteq X$ and $B \subseteq Y$.*

Theorem 4 (preimage arrow correctness). *lift_{pre} is a homomorphism.*

Corollary 1 (semantic correctness). *For all e , $\llbracket e \rrbracket_{\text{pre}} \equiv \text{lift}_{\text{pre}} \llbracket e \rrbracket_{\perp}$.*

While lifted bottom arrow computations behave intuitively, preimage arrow computations in general can be unruly. For example:

$$\begin{array}{l}
\text{unruly} : \text{Bool} \rightsquigarrow_{\text{pre}} \text{Bool} \\
\text{unruly } A := \langle \text{Bool} \setminus A, \lambda B. B \rangle
\end{array} \quad (19)$$

With this, $\text{ap}_{\text{pre}} (\text{unruly } \{\text{true}\}) \{\text{false}\} = \{\text{false}\} \cap (\text{Bool} \setminus \{\text{true}\}) = \{\text{false}\}$ —a “preimage” that does not even intersect the given domain $\{\text{true}\}$. We would like to be sure each $h : X \rightsquigarrow_{\text{pre}} Y$ always acts as if it computes preimages under some bottom arrow computation.

Definition 8 (preimage arrow law). *Let $h : X \rightsquigarrow_{\text{pre}} Y$. If there exists an $f : X \rightsquigarrow_{\perp} Y$ such that $h \equiv \text{lift}_{\text{pre}} f$, then h obeys the *preimage arrow law*.*

We assume from here on that the preimage arrow law holds for all $h : X \rightsquigarrow_{\text{pre}} Y$. By homomorphism of lift_{pre} , preimage arrow combinators return computations that obey this law. The preimage arrow law implies lift_{pre} is an epimorphism; by Theorem 1, the arrow laws hold.

5 Preimages Under Partial Functions

We have defined the top of our roadmap:

$$\begin{array}{ccc}
 X \rightsquigarrow_{\perp} Y & \xrightarrow{\text{lift}_{\text{pre}}} & X \rightsquigarrow_{\text{pre}} Y \\
 \eta_{\perp*} \downarrow & & \downarrow \eta_{\text{pre}*} \\
 X \rightsquigarrow_{\perp*} Y & \xrightarrow{\text{lift}_{\text{pre}*}} & X \rightsquigarrow_{\text{pre}*} Y
 \end{array} \tag{20}$$

so that lift_{pre} is a homomorphism. Now we move down each side and connect the bottom, in a way that makes every morphism a homomorphism.

5.1 Motivation

Probabilistic functions that may not terminate, but terminate with probability 1, are common. They come up not only when practitioners want to build data with random size or structure, but in simpler circumstances as well.

Suppose `random` retrieves a number $r \in [0, 1]$ at index j in an implicit random source r . The following function, which defines the well-known **geometric distribution** with parameter p , counts the number of times `random` $< p$ is false:

$$\text{geometric } p := \text{if } (\text{random} < p) \text{ } 0 \text{ } (1 + \text{geometric } p) \tag{21}$$

For any $p > 0$, `geometric p` may not terminate, but the probability of always taking the false branch is $(1 - p) \times (1 - p) \times (1 - p) \times \dots = 0$. Therefore, for $p > 0$, `geometric p` terminates with probability 1.

Suppose we interpret (21) as $h : R \rightsquigarrow_{\text{pre}} \mathbb{N}$, a preimage arrow computation from random sources in R to natural numbers, and that we have a probability measure $P \in \mathcal{P} R \rightarrow [0, 1]$. We could compute the probability of any output set $N \subseteq \mathbb{N}$ using $P(h R' N)$, where $R' \subseteq R$ and $P R' = 1$. We have three hurdles to overcome:

1. Ensuring $h R'$ terminates.
2. Ensuring each $r \in R$ contains enough random numbers.
3. Determining how `random` indexes numbers in r .

Ensuring $h R'$ terminates is the most difficult, but doing the other two will provide structure that makes it much easier.

5.2 Threading and Indexing

We clearly need bottom and preimage arrows that thread a random source. To ensure it contains enough random numbers, it should be infinite.

In a pure λ -calculus, random sources are typically infinite streams, threaded monadically: each computation receives and produces a random source. A little-used alternative is for the random source to be a tree, threaded applicatively: each computation receives, but does not produce, a random source. Combinators split the tree and pass subtrees to subcomputations.

With either alternative, for arrows, the resulting definitions are large, conceptually difficult, and hard to manipulate. Fortunately, assigning each subcomputation a unique index into a tree-shaped random source, and passing the random source unchanged, is relatively easy. To do this, we need an indexing scheme.

Definition 9 (binary indexing scheme). *Let J be an index set, $j_0 \in J$ a distinguished element, and $\text{left} : J \Rightarrow J$ and $\text{right} : J \Rightarrow J$ be total, injective functions. If for all $j \in J$, $j = \text{next } j_0$ for some finite composition next of left and right , then J, j_0, left and right define a **binary indexing scheme**.*

For example, let J be the set of lists of $\{0, 1\}$, $j_0 := \langle \rangle$, and $\text{left } j := \langle 0, j \rangle$ and $\text{right } j := \langle 1, j \rangle$. Alternatively, let J be the set of dyadic rationals in $(0, 1)$ (i.e. those with power-of-two denominators), $j_0 := \frac{1}{2}$ and

$$\begin{aligned} \text{left } (p/q) &:= (p - \tfrac{1}{2})/q \\ \text{right } (p/q) &:= (p + \tfrac{1}{2})/q \end{aligned} \tag{22}$$

With this alternative, left-to-right evaluation order can be made to correspond with the natural order ($<$) over J . In any case, J is countable, and can be thought of as a set of indexes into an infinite binary tree. Values of type $J \rightarrow A$ encode an infinite binary tree of A values as an infinite vector (i.e. total mapping).

5.3 Applicative, Associative Store Transformer

We thread a random store through bottom and preimage arrow computations by defining an **arrow transformer**: a type constructor that receives and produces an arrow type, and combinators for arrows of the produced type.

The **AStore** arrow type constructor takes a store type s and an arrow $x \rightsquigarrow_a y$:

$$\text{AStore } s \ (x \rightsquigarrow_a y) ::= J \Rightarrow (\langle s, x \rangle \rightsquigarrow_a y) \tag{23}$$

Reading the type, we see that computations receive an index $j \in J$ and produce a computation that receives a store as well as an x . Lifting extracts the x from the input pair and sends it on to the original computation:

$$\begin{aligned} \eta_{a^*} : (x \rightsquigarrow_a y) &\Rightarrow \text{AStore } s \ (x \rightsquigarrow_a y) \\ \eta_{a^*} f j &:= \text{arr}_a \text{ snd } \ggg_a f \end{aligned} \tag{24}$$

Because f never accesses the store, j is ignored.

$$\begin{array}{ll}
x \rightsquigarrow_{a^*} y ::= \text{AStore } s \ (x \rightsquigarrow_a y) ::= J \Rightarrow ((s, x) \rightsquigarrow_a y) & \text{ifte}_{a^*} : (x \rightsquigarrow_{a^*} \text{Bool}) \Rightarrow (x \rightsquigarrow_{a^*} y) \Rightarrow \\
& (x \rightsquigarrow_{a^*} y) \Rightarrow (x \rightsquigarrow_{a^*} y) \\
\text{arr}_{a^*} : (x \Rightarrow y) \Rightarrow (x \rightsquigarrow_{a^*} y) & \text{ifte}_{a^*} \ k_1 \ k_2 \ k_3 \ j := \\
\text{arr}_{a^*} := \eta_{a^*} \circ \text{arr}_a & \text{ifte}_a \ (k_1 \ (\text{left } j)) \\
& (k_2 \ (\text{left } (\text{right } j))) \\
& (k_3 \ (\text{right } (\text{right } j))) \\
(\ggg_{a^*}) : (x \rightsquigarrow_{a^*} y) \Rightarrow (y \rightsquigarrow_{a^*} z) \Rightarrow (x \rightsquigarrow_{a^*} z) & \text{lazy}_{a^*} : (1 \Rightarrow (x \rightsquigarrow_{a^*} y)) \Rightarrow (x \rightsquigarrow_{a^*} y) \\
(k_1 \ggg_{a^*} k_2) \ j := & \text{lazy}_{a^*} \ k \ j := \text{lazy}_a \ \lambda 0. k \ 0 \ j \\
(\text{arr}_a \text{ fst } \&\&\&_a \ k_1 \ (\text{left } j)) \ggg_a k_2 \ (\text{right } j) & \\
(\&\&\&_{a^*}) : (x \rightsquigarrow_{a^*} y_1) \Rightarrow (x \rightsquigarrow_{a^*} y_2) \Rightarrow (x \rightsquigarrow_{a^*} \langle y_1, y_2 \rangle) & \\
(k_1 \&\&\&_{a^*} k_2) \ j := k_1 \ (\text{left } j) \&\&\&_a k_2 \ (\text{right } j) & \text{---} \\
& \eta_{a^*} : (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_{a^*} y) \\
& \eta_{a^*} \ f \ j := \text{arr}_a \ \text{snd} \ \ggg_a \ f
\end{array}$$

Fig. 5: AStore (associative store) arrow transformer definitions.

Fig. 5 defines the remaining combinators. Each subcomputation receives `left j`, `right j`, or some other unique binary index. We thus think of programs interpreted as AStore arrows as being completely unrolled into an infinite binary tree, with each expression labeled with its tree index.

5.4 Partial, Probabilistic Programs

For probabilistic programs, we put an infinite binary tree in the store.

Definition 10 (random source). Let $R := J \rightarrow [0, 1]$. A *random source* is any infinite binary tree $r \in R$.

For partial programs, we need to ensure termination. One ultimately implementable way to do it is to have the store dictate which branch of each conditional, if any, can be taken.

Definition 11 (branch trace). A *branch trace* is any $t \in J \rightarrow \text{Bool}_\perp$ such that $t \ j = \text{true}$ or $t \ j = \text{false}$ for no more than finitely many $j \in J$.

Let $T \subset J \rightarrow \text{Bool}_\perp$ be the largest set of branch traces.

Let $X \rightsquigarrow_{a^*} Y ::= \text{AStore } (R \times T) \ (X \rightsquigarrow_a Y)$ be an AStore arrow type that threads both random stores and branch traces. We define a combinator random_{a^*} that returns the number at its tree index in the random source, and extend $\llbracket \cdot \rrbracket_{a^*}$ for arrows a^* for which random_{a^*} is defined:

$$\begin{aligned}
\text{random}_{a^*} : X \rightsquigarrow_{a^*} [0, 1] & \quad \llbracket \text{random} \rrbracket_{a^*} := \text{random}_{a^*} \\
\text{random}_{a^*} \ j := \text{arr}_a \ (\text{fst} \ggg \text{fst} \ggg \pi \ j) & \quad (25)
\end{aligned}$$

This is all we need to define probabilistic choice.

For partial programs, we define a combinator that reads branch traces:

$$\begin{aligned}
\text{branch}_{a^*} : X \rightsquigarrow_{a^*} \text{Bool} \\
\text{branch}_{a^*} \ j := \text{arr}_a \ (\text{fst} \ggg \text{snd} \ggg \pi \ j) & \quad (26)
\end{aligned}$$

Using branch_{a^*} , we define an if-then-else combinator that ensures its test expression agrees with the branch trace:

$$\begin{aligned} \text{agrees} &: \langle \text{Bool}, \text{Bool} \rangle \Rightarrow \text{Bool}_\perp \\ \text{agrees} \langle b_1, b_2 \rangle &:= \text{if } (b_1 = b_2) \ b_1 \ \perp \end{aligned} \quad (27)$$

$$\begin{aligned} \text{ifte}_{a^*}^\downarrow &: (x \rightsquigarrow_{a^*} \text{Bool}) \Rightarrow (x \rightsquigarrow_{a^*} y) \Rightarrow (x \rightsquigarrow_{a^*} y) \Rightarrow (x \rightsquigarrow_{a^*} y) \\ \text{ifte}_{a^*}^\downarrow k_1 k_2 k_3 j &:= \text{ifte}_a ((k_1 (\text{left } j) \ \&\&_a \text{branch}_{a^*} j) \ggg_a \text{arr}_a \text{agrees}) \\ &\quad (k_2 (\text{left } (\text{right } j))) \\ &\quad (k_3 (\text{right } (\text{right } j))) \end{aligned} \quad (28)$$

If the branch trace agrees with the test expression, it computes a branch; otherwise, it returns an error.

Because we assume every expression is well-defined (Definition 5), every expression must have its recurrences guarded by `if`. Thus, to ensure running their interpretations always terminates, we should only need to replace ifte_{a^*} with $\text{ifte}_{a^*}^\downarrow$. We define a new semantic function $\llbracket \cdot \rrbracket_{a^*}^\downarrow$ by

$$\llbracket \text{if } e_c \ e_t \ e_f \rrbracket_{a^*}^\downarrow := \text{ifte}_{a^*}^\downarrow \llbracket e_c \rrbracket_{a^*}^\downarrow \llbracket \text{lazy } e_t \rrbracket_{a^*}^\downarrow \llbracket \text{lazy } e_f \rrbracket_{a^*}^\downarrow \quad (29)$$

with the remaining rules similar to those of $\llbracket \cdot \rrbracket_{a^*}$.

For an **AStore** computation k , we obviously must run k on every branch trace in T and filter out \perp , or somehow find pairs of $\langle t, a \rangle$ (with $a : x$) for which `agrees` never returns \perp . Preimage **AStore** arrow computations do both.

Definition 12 (terminating, probabilistic arrows). *Define*

$$\begin{aligned} X \rightsquigarrow_{\perp^*} Y &::= \text{AStore } (R \times T) (X \rightsquigarrow_{\perp} Y) \\ X \rightsquigarrow_{\text{pre}^*} Y &::= \text{AStore } (R \times T) (X \rightsquigarrow_{\text{pre}} Y) \end{aligned} \quad (30)$$

as the type constructors for the **bottom*** and **preimage*** arrows.

Suppose $f := \llbracket e \rrbracket_{\perp^*}^\downarrow : X \rightsquigarrow_{\perp^*} Y$. Its domain is $X' := (R \times T) \times X$. We assume each $r \in R$ is random, but not $t \in T$ nor $a \in X$; therefore, neither T nor X should affect the probabilities of output sets. The probability of $B \subseteq Y$ is therefore

$$P (\text{image } (\text{fst} \ggg \text{fst}) (\text{preimage}_\perp f X' B)) \quad (31)$$

if f always terminates. Suppose $h := \llbracket e \rrbracket_{\text{pre}^*}^\downarrow$; then the probability is equivalently

$$P (\text{image } (\text{fst} \ggg \text{fst}) (\text{ap}_{\text{pre}} (h X') B)) \quad (32)$$

as long as h always terminates and computes correct preimages.

5.5 Correctness and Termination

We have two arrow lifts to prove homomorphic: one from pure computations to effectful (i.e. from those that do not access the store to those that do), and one from effectful computations to effectful. For both, we need **AStore** arrow equivalence to be more extensional.

Definition 13 (AStore arrow equivalence). *Two AStore arrow computations k_1 and k_2 are equivalent, or $k_1 \equiv k_2$, when $k_1 j \equiv k_2 j$ for all $j \in J$.*

Theorem 5 (pure AStore arrow correctness). *η_{a^*} is a homomorphism.*

Proof. Expand definitions and use arrow laws to factor out $\text{arr}_a \text{snd}$. \square

Corollary 2 (pure semantic correctness). *For all pure e , $\llbracket e \rrbracket_{a^*} \equiv \eta_{a^*} \llbracket e \rrbracket_a$.*

We need a lift between AStore arrows. Let $x \rightsquigarrow_{a^*} y ::= \text{AStore } s (x \rightsquigarrow_a y)$ and $x \rightsquigarrow_{b^*} y ::= \text{AStore } s (x \rightsquigarrow_b y)$. Define

$$\begin{aligned} \text{lift}_{b^*} : (x \rightsquigarrow_{a^*} y) &\Rightarrow (x \rightsquigarrow_{b^*} y) \\ \text{lift}_{b^*} f j &:= \text{lift}_b (f j) \end{aligned} \tag{33}$$

where $\text{lift}_b : (x \rightsquigarrow_a y) \Rightarrow (x \rightsquigarrow_b y)$.

Theorem 6 (effectful AStore arrow correctness). *If lift_b is an arrow homomorphism from a to b , then lift_{b^*} is an arrow homomorphism from a^* to b^* .*

Proof. For each of (12)–(15), distribute lift_b and rewrite in terms of lift_{b^*} . \square

Corollary 3 (preimage* arrow correctness). *$\text{lift}_{\text{pre}^*}$ is a homomorphism.*

Corollary 4 (effectful semantic correctness). *For all expressions e , $\llbracket e \rrbracket_{\text{pre}^*} \equiv \text{lift}_{\text{pre}^*} \llbracket e \rrbracket_{\perp^*}$ and $\llbracket e \rrbracket_{\perp^*}^{\downarrow} \equiv \text{lift}_{\text{pre}^*} \llbracket e \rrbracket_{\perp^*}^{\downarrow}$.*

To relate $\llbracket e \rrbracket_{a^*}^{\downarrow}$ computations to $\llbracket e \rrbracket_{a^*}$ computations, we need to find the largest domain on which they should agree.

Definition 14 (maximal domain). *Let $f : X \rightsquigarrow_{\perp^*} Y$. Its **maximal domain** is the largest $A^* \subseteq (R \times T) \times X$ for which $A^* = \{a \in A^* \mid f j_0 a \neq \perp\}$.*

Because $f j_0 a \neq \perp$ implies termination, A^* is a subset of the largest domain for which f terminates.

Theorem 7 (correct termination everywhere). *Let $\llbracket e \rrbracket_{\perp^*}^{\downarrow} : X \rightsquigarrow_{\perp^*} Y$ have maximal domain A^* , and $X' := (R \times T) \times X$. For all $a \in X'$, $A \subseteq X'$ and $B \subseteq Y$,*

$$\begin{aligned} \llbracket e \rrbracket_{\perp^*}^{\downarrow} j_0 a &= \text{if } (a \in A^*) (\llbracket e \rrbracket_{\perp^*} j_0 a) \perp \\ \text{ap}_{\text{pre}} (\llbracket e \rrbracket_{\text{pre}^*}^{\downarrow} j_0 A) B &= \text{ap}_{\text{pre}} (\llbracket e \rrbracket_{\text{pre}^*} j_0 (A \cap A^*)) B \end{aligned} \tag{34}$$

Proof. Roughly, every a for which $\llbracket e \rrbracket_{\perp^*}^{\downarrow} j_0 a$ terminates has an associated branch trace, and every a for which it loops does not. \square

In other words, preimages computed using $\llbracket \cdot \rrbracket_{\text{pre}^*}^{\downarrow}$ always terminate, never include inputs that give rise to errors or nontermination, and are correct.

$\text{id}_{\text{pre}} A := \langle A, \lambda B. B \rangle$	$\text{const}_{\text{pre}} b A := \langle \{b\}, \lambda B. \text{if } (B = \emptyset) \emptyset A \rangle$
$\text{fst}_{\text{pre}} A := \langle \text{proj}_1 A, \text{unproj}_1 A \rangle$	$\pi_{\text{pre}} j A := \langle \text{proj } j A, \text{unproj } j A \rangle$
$\text{snd}_{\text{pre}} A := \langle \text{proj}_2 A, \text{unproj}_2 A \rangle$	
<hr/>	
$\text{proj}_1 := \text{image fst}$	$\text{proj} : J \Rightarrow \text{Set } (J \rightarrow X) \Rightarrow \text{Set } X$
$\text{proj}_2 := \text{image snd}$	$\text{proj } j A := \text{image } (\pi j) A$
$\text{unproj}_1 A B := A \cap (B \times \text{proj}_2 A)$	$\text{unproj} : J \Rightarrow \text{Set } (J \rightarrow X) \Rightarrow \text{Set } X \Rightarrow \text{Set } (J \rightarrow X)$
$\text{unproj}_2 A B := A \cap (\text{proj}_1 A \times B)$	$\text{unproj } j A B := A \cap \prod_{i \in J} \text{if } (j = i) B (\text{proj } j A)$

Fig. 6: Preimage arrow lifts needed to interpret probabilistic programs.

6 Approximating Semantics

We would like to be able to compute preimages of uncountable sets, such as real intervals—but $\text{preimage}_{\perp} f A B$ is uncomputable for most uncountable sets A and B no matter how cleverly they are represented. Further, because pre , lift_{pre} and arr_{pre} are defined in terms of preimage_{\perp} , we cannot implement them.

Fortunately, we need only certain lifts. Fig. 6 gives explicit definitions for $\text{arr}_{\text{pre}} \text{id}$, $\text{arr}_{\text{pre}} \text{fst}$, $\text{arr}_{\text{pre}} \text{snd}$, $\text{arr}_{\text{pre}} (\text{const } b)$ and $\text{arr}_{\text{pre}} (\pi j)$. To implement them, we need to model sets in a way that $A = \emptyset$ is decidable, and the following are representable and finitely computable:

- $A \cap B$, \emptyset , $\{\text{true}\}$, $\{\text{false}\}$ and $\{b\}$ for every $\text{const } b$
- $A_1 \times A_2$, $\text{proj}_1 A$ and $\text{proj}_2 A$
- $J \rightarrow X$, $\text{proj } j A$ and $\text{unproj } j A B$

(35)

We first need to define families of sets under which these operations are closed.

Definition 15 (rectangular family). *Rect X denotes the **rectangular family** of subsets of X . Rect X must contain \emptyset and X , and be closed under finite intersections. Products must satisfy the following rules:*

$$\text{Rect } \langle X_1, X_2 \rangle = (\text{Rect } X_1) \boxtimes (\text{Rect } X_2) \quad (36)$$

$$\text{Rect } (J \rightarrow X) = (\text{Rect } X)^{\boxtimes J} \quad (37)$$

where the following operations lift cartesian products to sets of sets:

$$\mathcal{A}_1 \boxtimes \mathcal{A}_2 := \{A_1 \times A_2 \mid A_1 \in \mathcal{A}_1, A_2 \in \mathcal{A}_2\} \quad (38)$$

$$\mathcal{A}^{\boxtimes J} := \bigcup_{J' \subset J \text{ finite}} \left\{ \prod_{j \in J'} A_j \mid A_j \in \mathcal{A}, j \in J' \iff A_j \subset \bigcup \mathcal{A} \right\} \quad (39)$$

We additionally define $\text{Rect Bool} ::= \mathcal{P} \text{ Bool}$. It is easy to show the collection of all rectangular families is closed under products, projections, and unproj .

Further, all of the operations in (35) can be exactly implemented if finite sets are modeled directly, sets in an ordered space (such as \mathbb{R}) are modeled by intervals, and sets in $\text{Rect } \langle X_1, X_2 \rangle$ are modeled by pairs of type $\langle \text{Rect } X_1, \text{Rect } X_2 \rangle$. By (39), sets in $\text{Rect } (J \rightarrow X)$ have no more than finitely many projections that are proper subsets of X . They can be modeled by *finite* binary trees, where unrepresented projections are implicitly X .

The set of branch traces T is nonrectangular, but we can model T subsets by $J \rightarrow \text{Bool}_\perp$ rectangles, implicitly intersected with T .

Theorem 8 (T model). *If $T' \in \text{Rect } (J \rightarrow \text{Bool}_\perp)$ and $j \in J$, then $\text{proj } j (T' \cap T) = \text{proj } j T'$. Further, if $B \subseteq \text{Bool}_\perp$, then $\text{unproj } j (T' \cap T) B = \text{unproj } j T' B \cap T$.*

Rectangular families are not closed under (\cup) . For conditionals, then, we need a lattice join (\vee) with respect to (\subseteq) with the following additional properties:

$$\begin{aligned} (A_1 \times A_2) \vee (B_1 \times B_2) &= (A_1 \vee B_1) \times (A_2 \vee B_2) \\ (\prod_{j \in J} A_j) \vee (\prod_{j \in J} B_j) &= \prod_{j \in J} A_j \vee B_j \end{aligned} \quad (40)$$

If for every nonproduct type X , $\text{Rect } X$ is closed under (\vee) , then rectangular families are clearly closed under (\vee) . Further, for any A and B , $A \cup B \subseteq A \vee B$.

Fig. 7 defines approximating preimage arrows. Approximating preimage mapping operations (Fig. 7a) are defined in terms of lattice operations on rectangular families. Every approximating preimage arrow combinator (Fig. 7b) is defined the same way as its corresponding exact preimage arrow combinator, but using approximating preimage mapping operations instead of exact.

Most preimage* arrow combinators are AStore arrow combinators (Fig. 5). Fig. 7c defines $\text{random}'_{\text{pre}^*}$ and $\text{branch}'_{\text{pre}^*}$ without using the uncomputable $\text{arr}'_{\text{pre}^*}$, and $\text{ifte}^{\downarrow'}_{\text{pre}^*}$ for interpreting expressions using $\llbracket \cdot \rrbracket^{\downarrow'}_{\text{pre}^*}$ for guaranteed termination.

6.1 Correctness, Termination, and Preimage Refinement

Let $h := \llbracket e \rrbracket^{\downarrow}_{\text{pre}^*} : X \rightsquigarrow_{\text{pre}^*} Y$ and $h' := \llbracket e \rrbracket^{\downarrow'}_{\text{pre}^*} : X \rightsquigarrow'_{\text{pre}^*} Y$ for any expression e .

Theorem 9 (sound and terminating). $\text{ap}_{\text{pre}} (h \text{ j}_0 A) B \subseteq \text{ap}'_{\text{pre}} (h' \text{ j}_0 A) B$ for all $A \in \text{Rect } \langle \langle R, T \rangle, X \rangle$ and $B \in \text{Rect } Y$.

Theorem 10 (monotone). $\text{ap}'_{\text{pre}} (h' \text{ j}_0 A) B$ is monotone in both A and B .

Theorem 11 (decreasing). $\text{ap}'_{\text{pre}} (h' \text{ j}_0 A) B \subseteq A$ for all $A \in \text{Rect } \langle \langle R, T \rangle, X \rangle$ and $B \in \text{Rect } Y$.

Given these properties, we might try to compute preimages of B by computing preimages with respect to increasingly fine discretizations of A .

Definition 16 (preimage refinement algorithm). Let $B \in \text{Rect } Y$ and

$$\begin{aligned} \text{refine} : \text{Rect } \langle \langle R, T \rangle, X \rangle &\Rightarrow \text{Rect } \langle \langle R, T \rangle, X \rangle \\ \text{refine } A &:= \text{ap}'_{\text{pre}} (h' \text{ j}_0 A) B \end{aligned} \quad (41)$$

$$\begin{array}{ll}
X \xrightarrow{\text{pre}}' Y ::= \langle \text{Rect } Y, \text{Rect } Y \Rightarrow \text{Rect } X \rangle & \langle \cdot, \cdot \rangle'_{\text{pre}} : (X \xrightarrow{\text{pre}}' Y_1) \Rightarrow (X \xrightarrow{\text{pre}}' Y_2) \Rightarrow (X \xrightarrow{\text{pre}}' Y_1 \times Y_2) \\
\emptyset'_{\text{pre}} ::= \langle \emptyset, \lambda B. \emptyset \rangle & \langle \langle Y'_1, p_1 \rangle, \langle Y'_2, p_2 \rangle \rangle'_{\text{pre}} ::= \\
& \langle Y'_1 \times Y'_2, \lambda B. p_1 (\text{proj}_1 B) \cap p_2 (\text{proj}_2 B) \rangle \\
\text{ap}'_{\text{pre}} : (X \xrightarrow{\text{pre}}' Y) \Rightarrow \text{Rect } Y \Rightarrow \text{Rect } X & (\uplus'_{\text{pre}}) : (X \xrightarrow{\text{pre}}' Y) \Rightarrow (X \xrightarrow{\text{pre}}' Y) \Rightarrow (X \xrightarrow{\text{pre}}' Y) \\
\text{ap}'_{\text{pre}} \langle Y', p \rangle B := p (B \cap Y') & \langle Y'_1, p_1 \rangle \uplus'_{\text{pre}} \langle Y'_2, p_2 \rangle ::= \\
(\circ'_{\text{pre}}) : (Y \xrightarrow{\text{pre}}' Z) \Rightarrow (X \xrightarrow{\text{pre}}' Y) \Rightarrow (X \xrightarrow{\text{pre}}' Z) & \langle Y'_1 \vee Y'_2, \lambda B. \text{ap}'_{\text{pre}} \langle Y'_1, p_1 \rangle B \vee \text{ap}'_{\text{pre}} \langle Y'_2, p_2 \rangle B \rangle \\
\langle Z', p_2 \rangle \circ'_{\text{pre}} h_1 := \langle Z', \lambda C. \text{ap}'_{\text{pre}} h_1 (p_2 C) \rangle &
\end{array}$$

(a) Definitions for preimage mappings that compute rectangular covers.

$$\begin{array}{ll}
X \rightsquigarrow'_{\text{pre}} Y ::= \text{Rect } X \Rightarrow (X \xrightarrow{\text{pre}}' Y) & \text{ifte}'_{\text{pre}} : (X \rightsquigarrow'_{\text{pre}} \text{Bool}) \Rightarrow (X \rightsquigarrow'_{\text{pre}} Y) \Rightarrow \\
& (X \rightsquigarrow'_{\text{pre}} Y) \Rightarrow (X \rightsquigarrow'_{\text{pre}} Y) \\
(\ggg'_{\text{pre}}) : (X \rightsquigarrow'_{\text{pre}} Y) \Rightarrow (Y \rightsquigarrow'_{\text{pre}} Z) \Rightarrow (X \rightsquigarrow'_{\text{pre}} Z) & \text{ifte}'_{\text{pre}} h_1 h_2 h_3 A := \\
(h_1 \ggg'_{\text{pre}} h_2) A := \text{let } h'_1 := h_1 A & \text{let } h'_1 := h_1 A \\
& h'_2 := h_2 (\text{range}'_{\text{pre}} h'_1) \\
& \text{in } h'_2 \circ'_{\text{pre}} h'_1 \\
(\&\&\&'_{\text{pre}}) : (X \rightsquigarrow'_{\text{pre}} Y_1) \Rightarrow (X \rightsquigarrow'_{\text{pre}} Y_2) \Rightarrow (X \rightsquigarrow'_{\text{pre}} (Y_1, Y_2)) & \text{lazy}'_{\text{pre}} : (1 \Rightarrow (X \rightsquigarrow'_{\text{pre}} Y)) \Rightarrow (X \rightsquigarrow'_{\text{pre}} Y) \\
(h_1 \&\&\&'_{\text{pre}} h_2) A := \langle h_1 A, h_2 A \rangle'_{\text{pre}} & \text{lazy}'_{\text{pre}} h A := \text{if } (A = \emptyset) \emptyset'_{\text{pre}} (h \ 0 \ A)
\end{array}$$

(b) An approximating preimage arrow, defined using approximating preimage mappings.

$$\begin{array}{ll}
X \rightsquigarrow'_{\text{pre}^*} Y ::= \text{AStore } (R \times T) (X \rightsquigarrow'_{\text{pre}} Y) & \text{ifte}^{\text{ll}'}_{\text{pre}^*} : (X \rightsquigarrow'_{\text{pre}^*} \text{Bool}) \Rightarrow (X \rightsquigarrow'_{\text{pre}^*} Y) \Rightarrow (X \rightsquigarrow'_{\text{pre}^*} Y) \Rightarrow (X \rightsquigarrow'_{\text{pre}^*} Y) \\
\text{random}'_{\text{pre}^*} : X \rightsquigarrow'_{\text{pre}^*} [0, 1] & \text{ifte}^{\text{ll}'}_{\text{pre}^*} k_1 k_2 k_3 j := \\
\text{random}'_{\text{pre}^*} j := & \text{let } \langle C_k, p_k \rangle := k_1 (\text{left } j) A \\
& \langle C_b, p_b \rangle := \text{branch}_{\text{pre}^*} j A \\
& C_2 := C_k \cap C_b \cap \{\text{true}\} \\
& C_3 := C_k \cap C_b \cap \{\text{false}\} \\
& A_2 := p_k C_2 \cap p_b C_2 \\
& A_3 := p_k C_3 \cap p_b C_3 \\
\text{branch}'_{\text{pre}^*} : X \rightsquigarrow'_{\text{pre}^*} \text{Bool} & \text{in if } (C_b = \{\text{true}, \text{false}\}) \\
\text{branch}'_{\text{pre}^*} j := & \langle \top, \lambda B. A_2 \vee A_3 \rangle \\
& \text{fst}_{\text{pre}} \ggg'_{\text{pre}} \text{snd}_{\text{pre}} \ggg'_{\text{pre}} \pi_{\text{pre}} j \\
& (k_2 (\text{left } (\text{right } j)) A_2 \uplus'_{\text{pre}} k_3 (\text{right } (\text{right } j)) A_3) \\
\text{fst}'_{\text{pre}^*} := \eta'_{\text{pre}^*} \text{fst}_{\text{pre}}; \dots &
\end{array}$$

(c) Preimage* arrow combinators for probabilistic choice and guaranteed termination. Fig. 5 (AStore arrow transformer) defines η'_{pre^*} , (\ggg'_{pre^*}) , $(\&\&\&'_{\text{pre}^*})$, $\text{ifte}'_{\text{pre}^*}$ and $\text{lazy}'_{\text{pre}^*}$.

Fig. 7: Implementable arrows that approximate preimage arrows. Because arr_{pre} is generally uncomputable, there is no corresponding arr'_{pre} combinator. However, specific lifts such as $\text{fst}_{\text{pre}} := \text{arr}_{\text{pre}} \text{fst}$ are computable, and are defined in Fig. 6.

Define $\text{partition} : \text{Rect } \langle \langle R, T \rangle, X \rangle \Rightarrow \text{Set } (\text{Rect } \langle \langle R, T \rangle, X \rangle)$ to produce positive-measure, disjoint rectangles, and define

$$\begin{aligned} \text{refine}^* &: \text{Set } (\text{Rect } \langle \langle R, T \rangle, X \rangle) \Rightarrow \text{Set } (\text{Rect } \langle \langle R, T \rangle, X \rangle) \\ \text{refine}^* \mathcal{A} &:= \text{image refine } (\bigcup_{A \in \mathcal{A}} \text{partition } A) \end{aligned} \quad (42)$$

For any $A \in \text{Rect } \langle \langle R, T \rangle, X \rangle$, iterate refine^* on $\{A\}$.

Theorem 11 (decreasing) guarantees $\text{refine } A$ is never larger than A . Theorem 10 (monotonicity) guarantees refining a *partition* of A never does worse than refining A itself. Theorem 9 (soundness) guarantees the algorithm is sound: the preimage of B is always contained in the covering partition refine^* returns.

We would like it to be **complete** in the limit, up to null sets: covering partitions' measures should converge to the true preimage measure. Unfortunately, preimage refinement appears to compute the **Jordan outer measure** of a preimage, which is not always its measure.

We leave the conditions under which measures converge to future work, and for now, use algorithms that depend only on soundness.

7 Implementations

We have four implementations: one of the exact semantics, two direct implementations of the approximating semantics, and a less direct but more efficient implementation of the approximating semantics, which we call *Dr. Bayes*.

If sets are restricted to be finite, the exact semantics can be implemented directly in any practical λ -calculus. Computing exact preimages is very inefficient, even under the interpretations of very small programs. Still, we have found our Typed Racket [24] implementation useful for finding theorem candidates.

Given a rectangular set library, the approximating preimage arrows defined in Figs. 6 and 7b can be implemented with few changes in any practical λ -calculus. We have done so in Typed Racket and Haskell [1]. Both implementations' arrow combinator definitions are almost line-for-line transliterations from the figures.

All three direct implementations can currently be found at XXX: URL.

Our main implementation, *Dr. Bayes*, is written in Typed Racket. It consists of the semantic function $\llbracket \cdot \rrbracket_{a^*}$ from Fig. 1 and its extension $\llbracket \cdot \rrbracket_{a^*}^\downarrow$, the bottom* arrow as defined in Figs. 2 and 5, the approximating preimage and preimage* arrows as defined in Figs. 6 and 7, and algorithms to compute approximate probabilities. We use it to test the feasibility of solving real-world problems by computing approximate preimages.

Dr. Bayes's arrows operate on a monomorphic rectangular set data type. For data types and ad-hoc polymorphism, it includes tagged rectangles and disjoint unions. To overapproximate real intervals, it includes floating-point intervals. Finding the smallest covering rectangle for images and preimages under $\text{add}, \text{sub} : \langle \mathbb{R}, \mathbb{R} \rangle \Rightarrow \mathbb{R}$ and other monotone functions is straightforward. Given sub_{pre} and $\text{negative?}_{\text{pre}}$, inequalities such as (\leq_{pre}) are trivial. For the piecewise monotone $\text{mul}, \text{div} : \langle \mathbb{R}, \mathbb{R} \rangle \Rightarrow \mathbb{R}$, we distinguish monotone cases using ifte_{pre} .

Section 6.1 outlines preimage refinement: a discretization algorithm that seems to converge for programs that halt with probability 1, consisting of repeatedly shrinking and repartitioning a program’s domain. We do not use this algorithm directly in Dr. Bayes because it is inefficient: good accuracy requires fine discretization, which is exponential in the number of discretized axes.

Instead of enumerating partitions, Dr. Bayes samples from partitions of the random source, with time complexity linear in the number of samples and discretized axes. It uses expressions interpreted as bottom* arrow computations to reject samples that fall outside the true preimage set, and thus relies only on preimage refinement’s soundness.

XXX: specific problems: thermometer, stochastic ray tracing

8 Related Work

The forward phase in computing preimages takes a subdomain and returns an overapproximation of the function’s range for that subdomain. This clearly generalizes interval arithmetic [12] to all first-order algebraic types.

Our approximating semantics can be regarded as an abstract interpretation [7] where the concrete domain consists of measurable sets and the abstract domain consists of rectangular sets. In some ways, it is quite typical: it is sound, it labels expressions, the abstract domain is a lattice, and the exact semantics it approximates performs infinite computations. However, it is far from typical in other ways. It is used to run programs, not for static analysis. The abstraction boundaries are the if branches of completely unrolled, infinite programs, and are not fixed. There is no Kleene iteration. Infinite computations are done in a library of λ_{ZFC} -computable combinators, not by a semantic function. This cleanly separates the syntax from the semantics, and allows us to prove the exact semantics correct mostly by proving simple categorical properties.

Probabilistic languages can be approximately placed into two groups: those defined by an implementation, and those defined by a semantics.

Some languages defined by an implementation are probabilistic Scheme [15], BUGS [18], BLOG [20], BLAISE [5], Church [8], and Kiselyov’s embedded language for O’Caml [13]. The reports on these languages generally describe interpreters, compilers, and algorithms for sampling with probabilistic conditions. Recently, Wingate et al [28] have defined the semantics of nonstandard interpretations that enable efficient inference, but do not define the languages.

Early work in probabilistic language semantics is not motivated by Bayesian concerns, and thus does not address conditioning. Examples are Kozen [16], Hurd [10], Jones [11], Ramsey and Pfeffer [23], and Park [21]. Recent semantics work tackles conditioning, such as IBAL [22] and Fun [6]. While Fun’s original measure-theoretic semantics in particular looks promising, its implementations are so far based on probability densities. Thus, they cannot handle recursion, discontinuous programs, or arbitrary conditions.

9 Conclusions and Future Work

XXX: todo

Understanding the exact semantics, and implementing the approximating semantics, requires little more than basic set theory and some experience using combinator libraries in a pure λ -calculus.

the conditions under which the approximating semantics is complete in the limit, up to null sets

relation to type systems

constraints

sampling algorithms

different abstract domains

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