# Probabilistic Functional Programming

Donnacha Oisín Kidney July 18, 2018 Modeling Probability An Example Unclear Semantics Underpowered Monadic Modeling The Erwig And Kollmansberger Approach

Other Interpreters Theoretical Foundations Stochastic Lambda Calculus Giry Monad Other Applications **Differential Privacy** Conclusion

### Modeling Probability

How do we model stochastic and probabilistic processes in programming languages?

(apologies for the outdated language)

- 1. Mr. Jones has two children. The older child is a girl. What is the probability that both children are girls?
- 2. Mr. Smith has two children. At least one of them is a boy. What is the probability that both children are boys?

<sup>&</sup>lt;sup>1</sup>Martin Gardner. *The 2nd Scientific American Book of Mathematical Puzzles* & *Diversions*. University of Chicago Press ed. Chicago: University of Chicago Press, 1987. ISBN: 978-0-226-28253-4.

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Is the answer to 2  $\frac{1}{3}$  or  $\frac{1}{2}$ ?

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- Is the answer to  $2\frac{1}{3}$  or  $\frac{1}{2}$ ?

Part of the difficulty in the question is that it's ambiguous: can we use programming languages to lend some precision?

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Gardner originally wrote that the second question (perhaps surprisingly) has the answer  $\frac{1}{3}$ . However, he later acknowledged the question was ambiguous, and agreed that certain interpretations could correctly conclude its answer was  $\frac{1}{2}$ .

Using normal features built in to the language.

from random import randrange, choice

```
class Child:
    def __init__(self):
        self.gender = choice(['boy', 'girl'])
        self.age = randrange(18)
```

#### from operator import attrgetter

```
def mr_smith():
    child_1 = Child()
    child_2 = Child()
    assert child_1.gender == 'boy' or \
        child_2.gender == 'boy'
    return [child 1, child 2]
```

What contracts are guaranteed by probabilistic functions? What does it mean *exactly* for a function to be probabilistic? Why isn't the following<sup>2</sup> "random"?

<sup>&</sup>lt;sup>2</sup>Randall Munroe. *Xkcd: Random Number*. en. Title text: RFC 1149.5 specifies 4 as the standard IEEE-vetted random number. Feb. 2007. URL: https://xkcd.com/221/ (visited on 07/06/2018).

What about this?

```
children_1 = [Child(), Child()]
children_2 = [Child()] * 2
```

How can we describe the difference between **children\_1** and **children\_2**?



Probabilistic Functional Programming Modeling Probability Unclear Semantics

What about this?

children\_1 = [Child(), Child()]
children\_2 = [Child()] + 2

How can we describe the difference between children\_1 and children\_2?

The first runs two random processes; the second only one. Both have the same types, both look like they do the same thing. We need a good way to describe the difference between them. There are many more things we may want to do with probability distributions.

What about expectations?

```
def expect(predicate, process, iterations=100):
    success, tot = 0, 0
    for in range(iterations):
        try:
            success += predicate(process())
            tot += 1
        except AssertionError:
            pass
    return success / tot
```



This solution is both inefficient and inexact. Also, we may want to express other attributes of probability distributions: independence, for example.  $p\_1 \approx \frac{1}{2}$  $p\_2 \approx \frac{1}{3}$ 

# Monadic Modeling

### What we're approaching is a DSL, albeit an unspecified one.

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- How should we implement it? How can it be made efficient?

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- How should we implement it? How can it be made efficient?
- Can we glean any insights on the nature of probabilistic computations from the language? Are there any interesting symmetries?

First approach<sup>3</sup>:

**newtype** Dist  $a = Dist \{runDist :: [(a, \mathbb{R})]\}$ 

A distribution is a list of possible events, each tagged with a probability.

<sup>3</sup>Martin Erwig and Steve Kollmansberger. "Functional Pearls: Probabilistic Functional Programming in Haskell". In: *Journal of Functional Programming* 16.1 (2006), pp. 21–34. ISSN: 1469-7653, 0956-7968. DOI: **10.1017/S0956796805005721**. URL: http://web.engr. oregonstate.edu/~erwig/papers/abstracts.html%5C#JFP06a (visited on 09/29/2016). Probabilistic Functional Programming

└─Monadic Modeling

2018-07-18

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The Erwig And Kollmansberger Approach

First approach2:

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This representation only works for discrete distributions

We could (for example) encode a die as:

die :: Dist Integer die = Dist  $[(1, \frac{1}{6}), (2, \frac{1}{6}), (3, \frac{1}{6}), (4, \frac{1}{6}), (5, \frac{1}{6}), (6, \frac{1}{6})]$  This lets us encode (in the types) the difference between:

children\_1 :: [Dist Child] children\_2 :: Dist [Child]

```
def mr_smith():
    child_1 = Child()
    child_2 = Child()
    assert child_1.gender == 'boy' or \
        child_2.gender == 'boy'
    return [child_1, child_2]
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1. = (assignment)

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1. = (assignment)

2. assert

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```

- 1. = (assignment)
- 2. assert
- 3. return

Assignment expressions can be translated into lambda expressions:

 $let x = e_1 in e_2$  $\equiv (\lambda x. e_2) e_1$ 

In the context of a probabilistic language,  $e_1$  and  $e_1$  are distributions. So what we need to define is application: this is encapsulated by the "monadic bind":

```
(\gg) :: Dist a \rightarrow (a \rightarrow \text{Dist } b) \rightarrow \text{Dist } b
```

For a distribution, what's happening inside the  $\lambda$  is  $e_1$  given x. Therefore, the resulting probability is the product of the outer and inner probabilities.

 $xs \gg f = \text{Dist} [(y, xp \times yp) \\ | (x, xp) \leftarrow run\text{Dist } xs \\ , (y, yp) \leftarrow run\text{Dist} (f x)]$ 

Assertion is a kind of conditioning: given a statement about an event, it either occurs or it doesn't.

guard :: Bool → Dist () guard True = Dist [((),1)] guard False = Dist [] Return is the "unit" value for a distribution; the certain event, the unconditional distribution.

return ::  $a \rightarrow Dist a$ return x = Dist [(x, 1)]

```
mrSmith :: Dist [Child]
mrSmith = do
   child_1 \leftarrow child
   child_{2} \leftarrow child
   quard (gender child<sub>1</sub> \equiv Boy \lor gender child<sub>2</sub> \equiv Boy)
   return [child<sub>1</sub>, child<sub>2</sub>]
expect :: (a \to \mathbb{R}) \to \text{Dist } a \to \mathbb{R}
expect p xs = \frac{sum [p x \times xp|(x,xp) \leftarrow runDist xs]}{sum [xp|(-xp) \leftarrow runDist xs]}
probOf :: (a \rightarrow Bool) \rightarrow Dist a \rightarrow \mathbb{R}
probOf p = expect (\lambda x \rightarrow if p x then 1 else 0)
```
probOf (all (( $\equiv$ ) Girl  $\circ$  gender)) mrJones  $\equiv \frac{1}{2}$ probOf (all (( $\equiv$ ) Boy  $\circ$  gender)) mrSmith  $\equiv \frac{1}{3}$ 

# Once the semantics are described, different interpreters are easy to swap in.

```
data Decision = Decision { stick :: Bool
                                , switch :: Bool }
montyHall :: Dist Decision
montyHall = do
  car \leftarrow uniform [1..3]
  choice<sub>1</sub> \leftarrow uniform [1..3]
  let left = [door | door \leftarrow [1..3], door \neq choice_1]
  let open = head [door | door \leftarrow left, door \neq car]
  let choice<sub>2</sub> = head [door | door \leftarrow left, door \neq open]
  return (Decision { stick = car \equiv choice<sub>1</sub>
                       , switch = car \equiv choice<sub>2</sub>})
```

While we can interpret it in the normal way to solve the problem:

probOf stick montyHall  $\equiv \frac{1}{3}$ probOf switch montyHall  $\equiv \frac{2}{3}$ 

#### Monty Hall iii

We could alternatively draw a diagram of the process.



**Figure 1:** AST from Monty Hall problem. **1** is a win, **0** is a loss. The first column is what happens on a stick, the second is what happens on a loss.

### **Theoretical Foundations**

It is possible<sup>4</sup> to give measure-theoretic meanings to the operations described above.

$$\mathcal{M}\llbracket return x \rrbracket(A) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{otherwise} \end{cases}$$
(1)
$$\mathcal{M}\llbracket d \gg k \rrbracket(A) = \int_X \mathcal{M}\llbracket k(x) \rrbracket(A) d \mathcal{M}\llbracket d \rrbracket(x)$$
(2)

<sup>4</sup>Norman Ramsey and Avi Pfeffer. "Stochastic Lambda Calculus and Monads of Probability Distributions". In: 29th ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages. Vol. 37. ACM, 2002, pp. 154–165. URL: http://www.cs.tufts.edu/~nr/cs257/archive/normanramsey/pmonad.pdf (visited on 09/29/2016).

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- —Theoretical Foundations
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Stochastic Lambda Calculus

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http://www.cs.tufts.edu/~nr/cs257/archive/normanramsey/pmonad.pdf (visited on 09/29/2016).

return is the Dirac measure

#### Giry<sup>5</sup> gave a categorical interpretation of probability theory.

<sup>5</sup>Michèle Giry. "A Categorical Approach to Probability Theory". In: Categorical Aspects of Topology and Analysis. Ed. by A. Dold, B. Eckmann, and B. Banaschewski. Vol. 915. Berlin, Heidelberg: Springer Berlin Heidelberg, 1982, pp. 68–85. ISBN: 978-3-540-11211-2 978-3-540-39041-1. DOI: 10.1007/BFb0092872. URL: http://link.springer.com/10.1007/BFb0092872 (visited on 03/03/2017).

 $\begin{array}{ccc} X & \stackrel{f}{\longrightarrow} & Y \\ & & & \downarrow g \\ g \circ f & & \downarrow g \\ & & & Z \end{array}$ 



Objects 
$$Ob(C) = \{X, Y, Z\}$$



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Arrows form a monoid under composition



$$(h \circ g) \circ f = h \circ (g \circ f) \qquad (3)$$

 $A \supset id_A \qquad \forall A.A \in \mathsf{Ob}(\mathsf{C}) \exists id_A : \mathsf{hom}_{\mathsf{C}}(A,A)$ (4)



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**Example Set** is the category of sets, where objects are sets, and arrows are functions. The category of (small) categories, **Cat**, has morphisms called Functors.

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Functors which embed categories into themselves are called Endofunctors.

In the category of Endofunctors, Endo, a Monad is a triple of:

- 1. An Endofunctor *m*,
- 2. A natural transformation:

$$\eta: \mathsf{A} \to m(\mathsf{A}) \tag{5}$$

This is an operation which embeds an object.

3. Another natural transformation:

$$\mu: m^2(A) \to m(A) \tag{6}$$

This collapses two layers of the functor.

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We can construct a functor  $(\mathcal{P})$ , which, for any given measurable space  $\mathcal{M}$ , is the space of all possible measures on it.

 $\mathcal{P}(\mathcal{M})$  is itself a measurable space: measuring is integrating over some variable  $\mathfrak{a}$  in  $\mathcal{M}$ .

#### In code (we restrict to measurable functions):

**newtype** Measure a = Measure  $((a \rightarrow \mathbb{R}) \rightarrow \mathbb{R})$ 

<sup>&</sup>lt;sup>6</sup>Jared Tobin. *Implementing the Giry Monad*. Feb. 2017. URL: https://jtobin.io/giry-monad-implementation (visited on 06/30/2018).

In code (we restrict to measurable functions):

**newtype** Measure a = Measure  $((a \rightarrow \mathbb{R}) \rightarrow \mathbb{R})$ 

We also get  $\eta$  and  $\mu$ :

integrate :: Measure  $a \to (a \to \mathbb{R}) \to \mathbb{R}$ integrate (Measure m) f = m f

return ::  $a \rightarrow Measure a$ 

return x = Measure ( $\lambda$ measure  $\rightarrow$  measure x)

 $(\gg) :: Measure \ a \to (a \to Measure \ b) \to Measure \ b$  $xs \gg f = Measure \ (\lambda measure \to integrate \ xs$  $(\lambda x \to integrate \ (f \ x)$  $(\lambda y \to measure \ y)))$ 

<sup>6</sup>Jared Tobin. *Implementing the Giry Monad*. Feb. 2017. URL: https://jtobin.io/giry-monad-implementation (visited on 06/30/2018). **Other Applications** 

## It has been shown<sup>7</sup> that the semantics of the probability monad suitable encapsulate *differential privacy*.

<sup>7</sup>Jason Reed and Benjamin C. Pierce. "Distance Makes the Types Grow Stronger: A Calculus for Differential Privacy". In: *ACM Sigplan Notices*. Vol. 45. ACM, 2010, pp. 157–168. URL: http://dl.acm.org/citation.cfm?id=1863568 (visited on 03/01/2017).

# LINQ<sup>8</sup> is an API which provides a monadic syntax for performing queries (sql, etc.)

PINQ<sup>9</sup> extends this to provide *differentially private* queries.

<sup>8</sup>Don Box and Anders Hejlsberg. *LINQ: .NET Language Integrated Query.* en. Feb. 2007. URL:

https://msdn.microsoft.com/en-us/library/bb308959.aspx
(visited on 07/09/2018).

<sup>9</sup>Frank McSherry. "Privacy Integrated Queries". In: *Communications of the* ACM (Sept. 2010). URL: https://www.microsoft.com/enus/research/publication/privacy-integrated-queries-2/.

### Conclusion