Probabilistic Functional Programming

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Modeling Probability

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

The Boy-Girl Paradox

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?

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

An Ad-Hoc Solution i

Using normal features built in to the language.

```python
from random import randrange, choice

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

An Ad-Hoc Solution ii

```python
from operator import attrgetter

def mr_jones():
    child_1 = Child()
    child_2 = Child()
    eldest = max(child_1, child_2,
                 key=attrgetter('age'))
    assert eldest.gender == 'girl'
    return [child_1, child_2]
```

An Ad-Hoc Solution iii

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

Unclear semantics

What contracts are guaranteed by probabilistic functions?
What does it mean *exactly* for a function to be probabilistic?
Why isn't the following[1] "random"?

```
int getRandomNumber()
{
  return 4; // chosen by fair dice roll.
            // guaranteed to be random.
}
```

[1] 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`?

Underpowered

There are many more things we may want to do with probability distributions.

What about expectations?

```python
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
```

The Ad-Hoc Solution

```python
p_1 = expect(
    lambda children: all(child.gender == 'girl'
                         for child in children),
    mr_jones)
p_2 = expect(
    lambda children: all(child.gender == 'boy'
                         for child in children),
    mr_smith)
```

$$\texttt{p\_1} \approxeq \frac{1}{2}$$
$$\texttt{p\_2} \approxeq \frac{1}{3}$$

Monadic Modeling

A DSL

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Three questions for this DSL:

- Why should we implement it? What is it useful for?
- 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?

The Erwig And Kollmansberger Approach

First approach[2]:

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

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

[2] 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).

We could (for example) encode a die as:

$$\mathit{die} :: \mathit{Dist}\ \mathit{Integer}$$
$$\mathit{die} = \mathit{Dist}\ [(1, \tfrac{1}{6}), (2, \tfrac{1}{6}), (3, \tfrac{1}{6}), (4, \tfrac{1}{6}), (5, \tfrac{1}{6}), (6, \tfrac{1}{6})]$$

This lets us encode (in the types) the difference between:

```
children_1 :: [Dist Child]
children_2 :: Dist [Child]
```

As we will use this as a DSL, we need to define the language features we used above:

```python
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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def mr_smith():
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```

1. = (assignment)

As we will use this as a DSL, we need to define the language features we used above:

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def mr_smith():
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```

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

Assignment i

Assignment expressions can be translated into lambda expressions:

$$\begin{aligned} & \textbf{let } x = e_1 \textbf{ in } e_2 \\ \equiv & \\ & (\lambda x.e_2)\ e_1 \end{aligned}$$

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”:

$$(\gg\!=) :: \mathit{Dist}\ a \to (a \to \mathit{Dist}\ b) \to \mathit{Dist}\ b$$

Assignment ii

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

$$\begin{aligned} xs \gg\!= f = \mathit{Dist}\ & [\,(y, xp \times yp) \\ & \mid (x, xp) \leftarrow \mathit{runDist}\ xs \\ & ,\ (y, yp) \leftarrow \mathit{runDist}\ (f\ x)] \end{aligned}$$

Assertion

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

$$\begin{aligned}
&\mathit{guard} :: \mathit{Bool} \rightarrow \mathit{Dist}\ ()\\
&\mathit{guard}\ \mathit{True}\ \ = \mathit{Dist}\ [((),1)]\\
&\mathit{guard}\ \mathit{False} = \mathit{Dist}\ [\,]
\end{aligned}$$

Return

Return is the “unit” value for a distribution; the certain event, the unconditional distribution.

$$\begin{aligned}&\mathit{return} :: a \to \mathit{Dist}\ a\\ &\mathit{return}\ x = \mathit{Dist}\ [(x, 1)]\end{aligned}$$

Putting it all Together

```
mrSmith :: Dist [Child]
mrSmith = do
  child1 ← child
  child2 ← child
  guard (gender child1 ≡ Boy ∨ gender child2 ≡ Boy)
  return [child1, child2]
```

$expect :: (a \rightarrow \mathbb{R}) \rightarrow Dist\ a \rightarrow \mathbb{R}$

$expect\ p\ xs = \frac{sum\ [p\ x \times xp \mid (x, xp) \leftarrow runDist\ xs]}{sum\ [xp \mid (\_, xp) \leftarrow runDist\ xs]}$

$probOf :: (a \rightarrow Bool) \rightarrow Dist\ a \rightarrow \mathbb{R}$

$probOf\ p = expect\ (\lambda x \rightarrow \mathbf{if}\ p\ x\ \mathbf{then}\ 1\ \mathbf{else}\ 0)$

$$\mathit{probOf}\ (\mathit{all}\ ((\equiv)\ \mathit{Girl} \circ \mathit{gender}))\ \mathit{mrJones} \equiv \frac{1}{2}$$
$$\mathit{probOf}\ (\mathit{all}\ ((\equiv)\ \mathit{Boy} \circ \mathit{gender}))\ \mathit{mrSmith} \equiv \frac{1}{3}$$

Alternative Interpreters

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

Monty Hall i

```
data Decision = Decision {stick  :: Bool
                         , switch :: Bool}
montyHall :: Dist Decision
montyHall = do
  car         ← uniform [1 .. 3]
  choice₁     ← uniform [1 .. 3]
  let left    = [door | door ← [1 .. 3], door ≢ choice₁]
  let open    = head [door | door ← left, door ≢ car]
  let choice₂ = head [door | door ← left, door ≢ open]
  return (Decision {stick  = car ≡ choice₁
                   , switch = car ≡ choice₂})
```

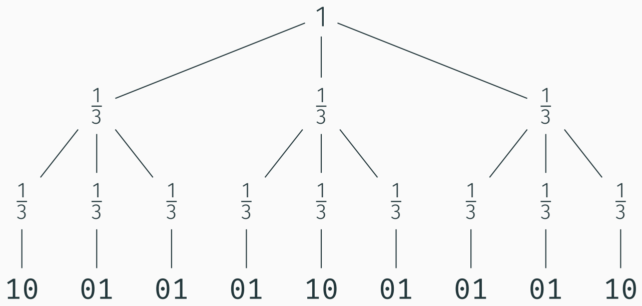
Monty Hall ii

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

$$\begin{aligned} &\mathit{probOf}\ \mathit{stick}\quad \mathit{montyHall} \equiv \frac{1}{3} \\ &\mathit{probOf}\ \mathit{switch}\ \mathit{montyHall} \equiv \frac{2}{3} \end{aligned}$$

Monty Hall iii

We could alternatively draw a diagram of the process.



1
$\frac{1}{3}$
$\frac{1}{3}$
$\frac{1}{3}$
$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$
10 01 01 01 10 01 01 01 10

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

Stochastic Lambda Calculus

It is possible[3] to give measure-theoretic meanings to the operations described above.

$$\mathcal{M}\left[\!\left[\textit{return}\ x\right]\!\right](A) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$\mathcal{M}\left[\!\left[d \gg\!= k\right]\!\right](A) = \int_X \mathcal{M}\left[\!\left[k(x)\right]\!\right](A)\, d\mathcal{M}\left[\!\left[d\right]\!\right](x) \tag{2}$$

[3] 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/norman-ramsey/pmonad.pdf` (visited on 09/29/2016).

The Giry Monad

Giry[4] gave a categorical interpretation of probability theory.

[4] 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).

Categories, Quickly

A category $\mathbf{C}$ has:

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Objects $\mathrm{Ob}(\mathsf{C})$

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Arrows form a monoid under composition:

$$(\mathsf{hom}_{\mathsf{C}}(c,d) \circ \mathsf{hom}_{\mathsf{C}}(b,c)) \circ \mathsf{hom}_{\mathsf{C}}(a,b) = \mathsf{hom}_{\mathsf{C}}(c,d) \circ (\mathsf{hom}_{\mathsf{C}}(b,c) \circ \mathsf{hom}_{\mathsf{C}}(a,b)) \tag{3}$$

$$\forall a . a \in \mathsf{Ob}(\mathsf{C}) \; \exists \; id_a : \mathsf{hom}_{\mathsf{C}}(a,a) \tag{4}$$

Categories, Quickly

A category **C** has:

Objects	$\mathsf{Ob}(\mathsf{C})$
Arrows	$\mathsf{hom}_{\mathsf{C}}$

Arrows form a monoid under composition:

$$(\mathsf{hom}_{\mathsf{C}}(c,d) \circ \mathsf{hom}_{\mathsf{C}}(b,c)) \circ \mathsf{hom}_{\mathsf{C}}(a,b) = \mathsf{hom}_{\mathsf{C}}(c,d) \circ (\mathsf{hom}_{\mathsf{C}}(b,c) \circ \mathsf{hom}_{\mathsf{C}}(a,b)) \quad (3)$$

$$\forall a.a \in \mathsf{Ob}(\mathsf{C})\ \exists\ id_a : \mathsf{hom}_{\mathsf{C}}(a,a) \quad (4)$$

Set is the category of sets, where objects are sets, and arrows are functions.

Functors

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Functors which embed categories into themselves are called Endofunctors.

Monads

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

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

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

   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.

The Category of Measurable Spaces

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The monad is from above:

$$\eta = \mathit{return} \tag{7}$$

$$\mu(P) = P \gg\!= \mathit{id} \tag{8}$$

Implementation

The implementation of the Giry monad is quite direct:

$$\textbf{newtype}\ \mathit{Measure}\ a = \mathit{Measure}\ ((a \to \mathbb{R}) \to \mathbb{R})$$

Other Applications

Differential Privacy

It has been shown[5] that the semantics of the probability monad suitable encapsulate *differential privacy*.

[5] 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).

PINQ

LINQ[6] is an API which provides a monadic syntax for performing queries (sql, etc.)

PINQ[7] extends this to provide *differentially private* queries.

[6] 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).

[7] Frank McSherry. “Privacy Integrated Queries”. In: *Communications of the ACM* (Sept. 2010). URL: `https://www.microsoft.com/en-us/research/publication/privacy-integrated-queries-2/`.

Conclusion