

Conditioning and density, mathematically and computationally

Chung-chieh Shan (with Wazim Mohammed Ismail)



INDIANA UNIVERSITY

Mathematical Foundations of Programming Semantics

June 14, 2014

Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

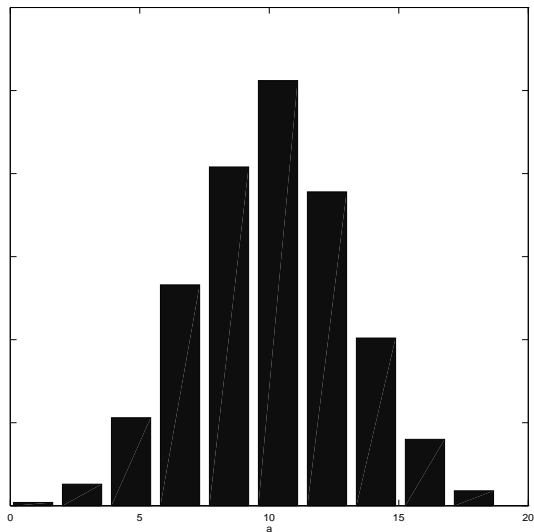
Generative story

Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

Generative story

```
a <- normal 10 3
```

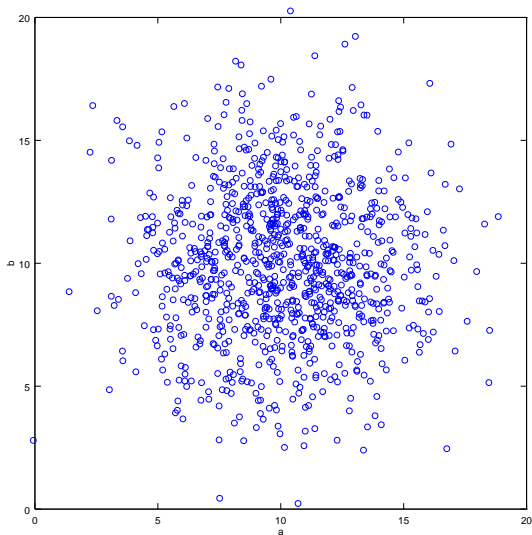


Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

Generative story

```
a <- normal 10 3  
b <- normal 10 3
```

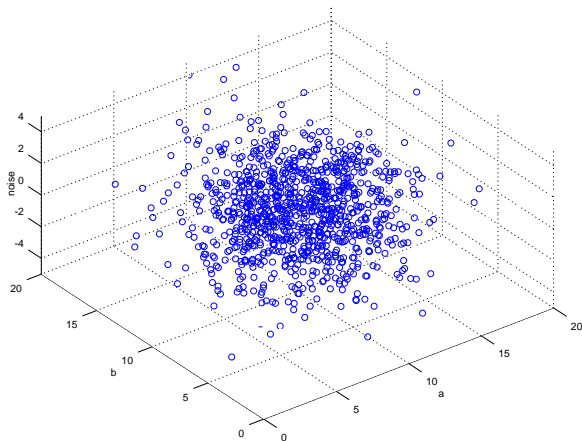


Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

Generative story

```
a <- normal 10 3  
b <- normal 10 3  
l <- normal 0 2
```



Probabilistic programming

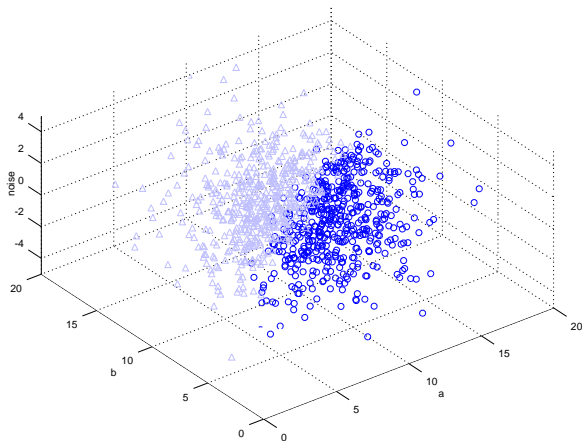
Alice beat Bob at a game. Is she better than him at it?

Generative story

```
a <- normal 10 3  
b <- normal 10 3  
l <- normal 0 2
```

Observed effect

```
condition (a-b > l)
```



Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

Generative story

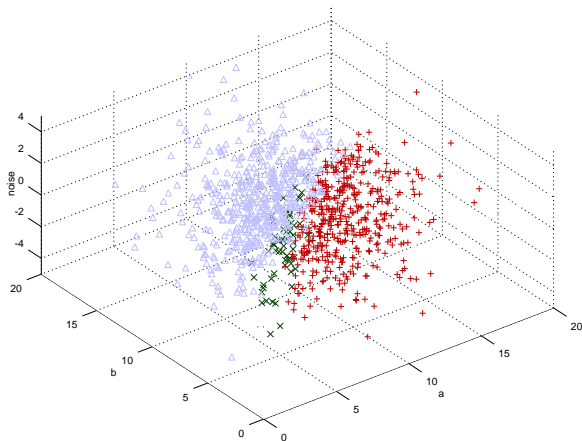
```
a <- normal 10 3  
b <- normal 10 3  
l <- normal 0 2
```

Observed effect

```
condition (a-b > l)
```

Hidden cause

```
return (a > b)
```



Probabilistic programming

Alice beat Bob at a game. Is she better than him at it?

Generative story

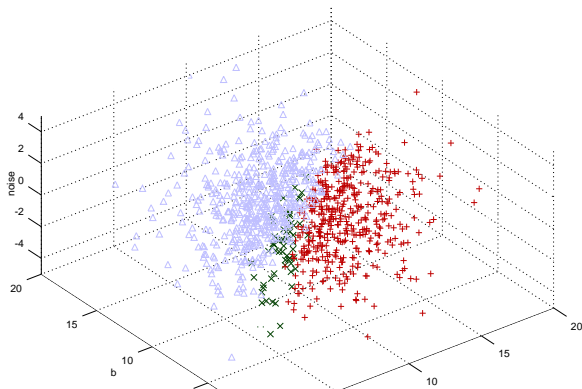
```
a <- normal 10 3  
b <- normal 10 3  
l <- normal 0 2
```

Observed effect

```
condition (a-b > l)
```

Hidden cause

```
return (a > b)
```



Denoted measure:

$$\lambda c. \int da \int db \int dl \langle a - b > l \rangle c(a > b) \\ N(10,3) \ N(10,3) \ N(0,2)$$

Importance sampling

Alice beat Bob at a game. Is she better than him at it?

Generative story

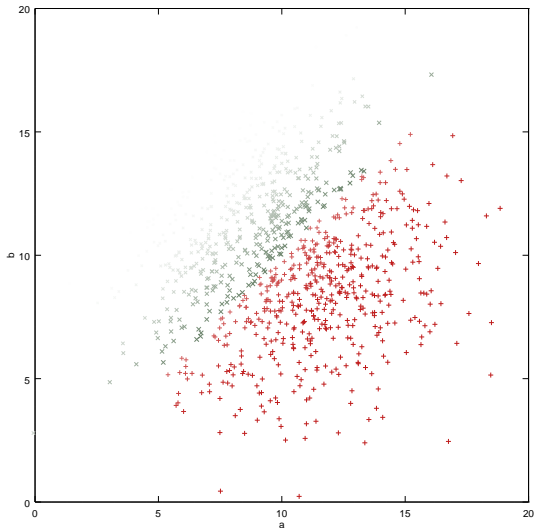
```
a <- normal 10 3
```

```
b <- normal 10 3
```

```
weight (1 + erf( $\frac{a-b}{2\sqrt{2}}$ ))/2
```

Hidden cause

```
return (a > b)
```



Importance sampling

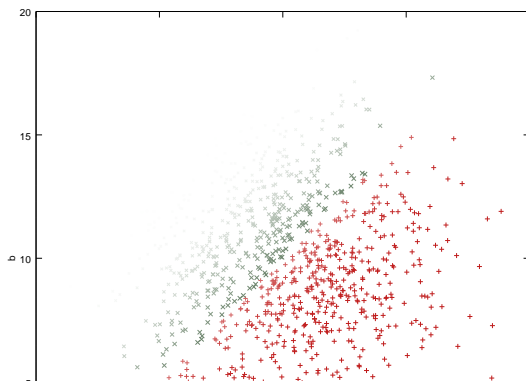
Alice beat Bob at a game. Is she better than him at it?

Generative story

```
a <- normal 10 3  
b <- normal 10 3  
weight (1 + erf( $\frac{a-b}{2\sqrt{2}}$ ))/2
```

Hidden cause

```
return (a > b)
```



Denoted measure:

$$\lambda c. \int_{N(10,3)} da \int_{N(10,3)} db \frac{1 + \text{erf}\left(\frac{a-b}{2\sqrt{2}}\right)}{2} c(a > b)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

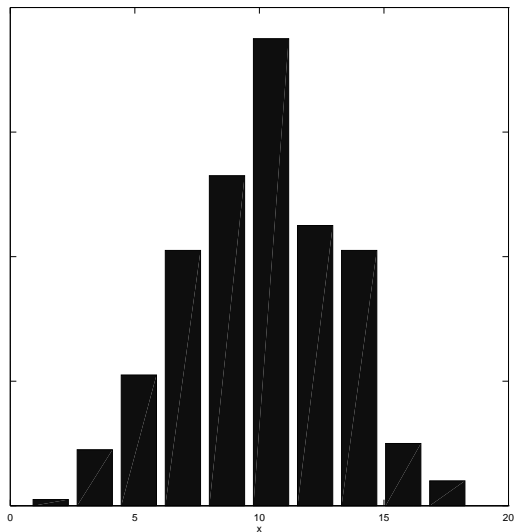
Generative story

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal 10 3
```

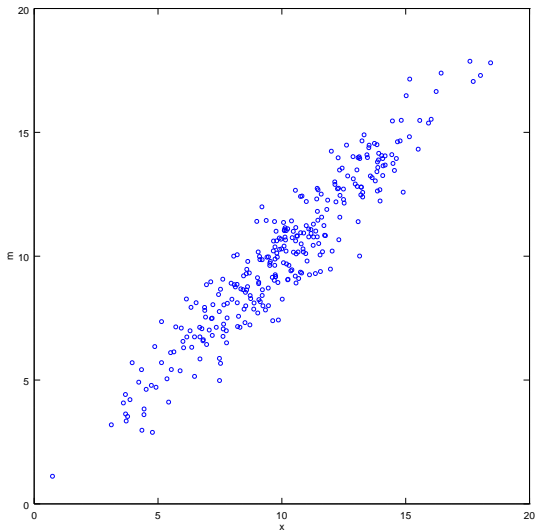


Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal    10 3  
m <- normal    x 1
```

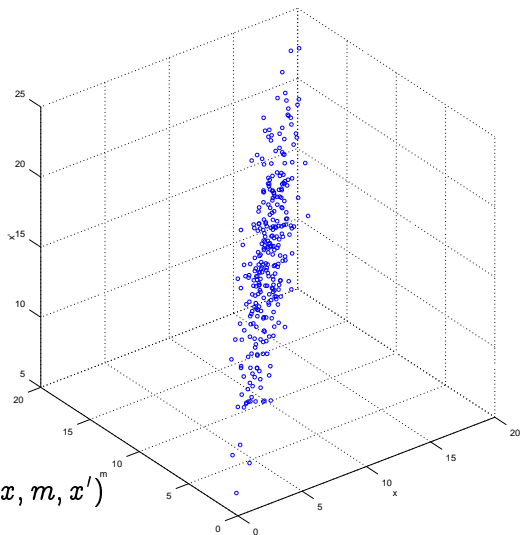


Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal    10 3  
m <- normal    x 1  
x' <- normal (x+5) 2
```



Denoted measure:

$$\lambda c. \int dx \int dm \int dx' c(x, m, x')^m$$
$$N(10,3) \quad N(x,1) \quad N(x+5,2)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal    10 3  
m <- normal    x 1  
x' <- normal (x+5) 2
```

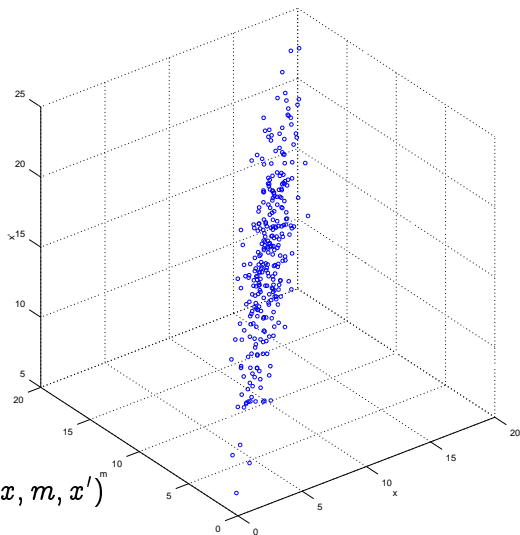
Observed effect

`condition (m = 9)`

Denoted measure:

$$\lambda_{c.} \int dx \int dm \int dx' c(x, m, x')^m$$

$N(10,3) \quad N(x,1) \quad N(x+5,2)$



Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x ← normal(10, 3)  m ← normal(10, √10)
m ← normal(x, 1)    x ← normal((9/10)m + (1/10)10, √(9/10))
x' ← normal(x+5, 2)
```

Observed effect

condition (m = 9)

Denoted measure:

$$\lambda_{\mathcal{C}} \int dm \int dx \int dx' c(x, m, x')$$
$$N(10, \sqrt{10}) \quad N\left(\frac{9}{10}m + \frac{1}{10}10, \sqrt{\frac{9}{10}}\right) \quad N(x+5, 2)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal(10, 3)  m <- normal(10, sqrt(10))  let m = 9
m <- normal(x, 1)    x <- normal((9/10)m + (1/10)10, sqrt(9/10))
x' <- normal(x+5, 2)
```

Observed effect

~~condition(m = 9)~~

Denoted **conditional** measure:

$$\lambda m. \lambda c. \int dx \int dx' c(x, m, x') N\left(\frac{9}{10}m + \frac{1}{10}10, \sqrt{\frac{9}{10}}\right) N(x+5, 2)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal 91/10 sqrt(9/10)
x' <- normal (x+5) 2
```

Denoted **marginal** measure:

$$\lambda c. \int dx \int dx' c(x, x') \\ N\left(\frac{91}{10}, \sqrt{\frac{9}{10}}\right) N(x+5, 2)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x <- normal 91/10 sqrt(9/10)
x' <- normal (x+5) 2
```

Hidden cause

```
return x'
```

Denoted **marginal** measure:

$$\lambda c. \int dx \int dx' c(x') \\ N\left(\frac{91}{10}, \sqrt{\frac{9}{10}}\right) N(x+5, 2)$$

Conditioning on a real number

The bike was moving near location 9. Where's it now?

Generative story

```
x' <- normal  $\frac{141}{10}$   $\sqrt{\frac{49}{10}}$ 
```

Hidden cause

```
return x'
```

Denoted **marginal** measure:

$$\lambda c. \int dx' c(x')$$
$$N\left(\frac{141}{10}, \sqrt{\frac{49}{10}}\right)$$

Importance sampling

Each sample has an *importance weight*

Importance sampling

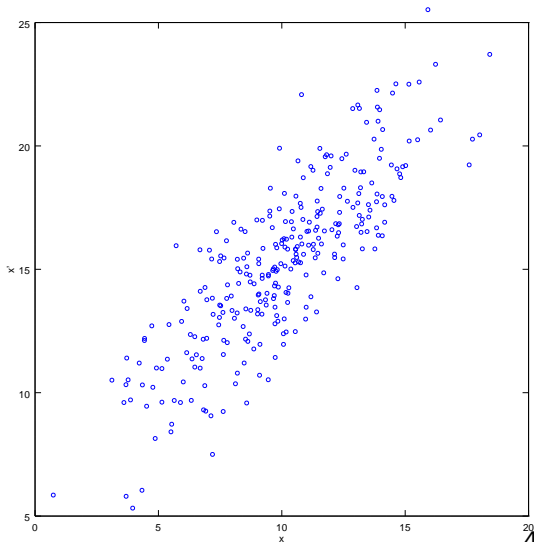
Each sample has an *importance weight*

Generative story

```
x <- normal    10 3  
m <- normal    x 1  
x' <- normal (x+5) 2
```

Observed effect

```
condition (m = 9)
```



Importance sampling

Each sample has an *importance weight*:

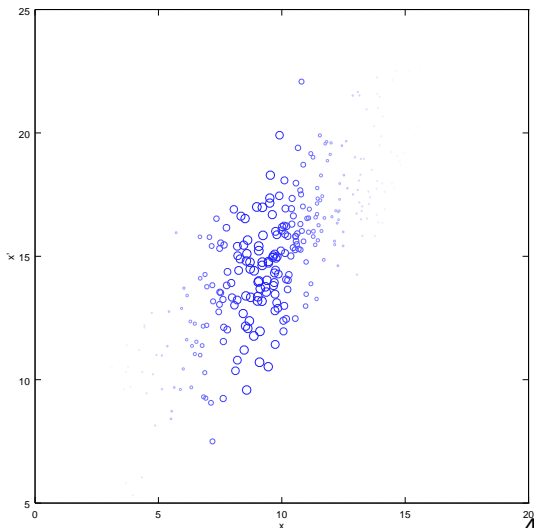
How much did we rig our random choices to avoid rejection?

Generative story

```
x <- normal 10 3  
weight  $e^{-(9-x)^2/2} / \sqrt{2\pi}$   
x' <- normal (x+5) 2
```

Denoted measure:

$$\lambda c. \int dx \frac{e^{-(9-x)^2/2}}{\sqrt{2\pi}} \\ N(10,3) \int dx' c(x, m, x') \\ N(x+5,2)$$



Probability or density?

Generative story

```
x <- flip True False
m <- (if x then flip 0 1
      else normal 0 1)
```

Observed effect

```
condition (m = 1)
```

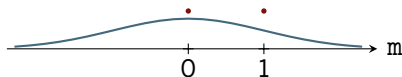
Hidden cause

```
return x
```


Probability or density?

Generative story

```
x <- flip True False  
weight (if x then 1/2  
        else  $e^{-1/2}/\sqrt{2\pi}$ )
```



Hidden cause

```
return x
```


Ambient measures

Let μ be a measure over pairs (x, m) .

$$\begin{aligned} \mu &= \dots \leftarrow \dots &= \lambda c. \iint \dots c(x, m) \\ &\quad \dots \leftarrow \dots \\ &\quad \dots \\ &\quad \text{return } (x, m) \end{aligned}$$

Condition μ **on** m = Express μ by choosing m first!
(easy when m is drawn from a fixed measure)

$$\begin{aligned} \mu &= m \leftarrow \dots &= \lambda c. \int dm \int \dots c(x, m) \\ &\quad \dots \leftarrow \dots \\ &\quad \dots \\ &\quad \text{return } (x, m) \end{aligned}$$

It doesn't matter what the ambient measure τ is,
but there must be *one*, such as Lebesgue.

Ambient measures

Let μ be a measure over pairs (x, m) .

$$\begin{array}{l} \mu = \dots \leftarrow \dots \\ \quad \dots \leftarrow \dots \\ \quad \dots \\ \quad \text{return } (x, m) \end{array} = \lambda c. \iint \dots c(x, m)$$

Condition μ on m = Express μ by choosing m first!
(easy when m is drawn from a fixed measure)

$$\begin{array}{l} \mu = m \leftarrow \dots \\ \quad \dots \leftarrow \dots \\ \quad \dots \\ \quad \text{return } (x, m) \end{array} = \lambda c. \int dm \int \dots c(x, m)$$

It doesn't matter what the ambient measure τ is,
but there must be *one*, such as Lebesgue.

Ambient measures

Let μ be a measure over pairs (x, m) .

$$\begin{array}{l} \mu = \dots \leftarrow \dots \\ \quad \dots \leftarrow \dots \\ \quad \dots \\ \text{return } (x, m) \end{array} = \lambda c. \iint \dots c(x, m)$$

Condition μ on m = Express μ by choosing m first!
(easy when m is drawn from a fixed measure)

$$\begin{array}{l} \nu(m) = \textcolor{brown}{m} \text{---} \textcolor{brown}{\leftarrow} \textcolor{brown}{\tau} \text{---} \\ \quad \dots \leftarrow \dots \\ \quad \dots \\ \text{return } (x, m) \end{array} = \lambda c. \textcolor{brown}{\int} \textcolor{brown}{d\textcolor{brown}{m}} \int \dots c(x, m)$$

It doesn't matter what the ambient measure τ is,
but there must be *one*, such as Lebesgue.

Discrete importance sampling revisited

```
a <- normal 10 3
```

```
b <- normal 10 3
```

```
l <- normal 0 2
```

```
w <- dirac (a-b > l) ==
```

```
a <- normal 10 3
```

```
b <- normal 10 3
```

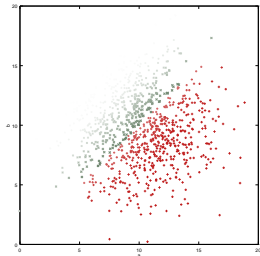
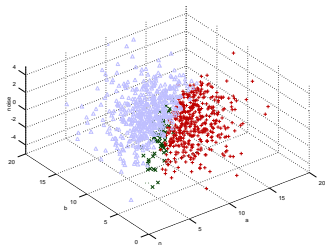
```
l <- normal 0 2
```

```
w <- counting
```

```
weight (if a-b > l then 1  
        else 0)
```

```
return (a > b)
```

```
return (a > b)
```



probability density (absolute continuity) w.r.t. counting

Discrete importance sampling revisited

```
a <- normal 10 3
```

```
b <- normal 10 3
```

```
l <- normal 0 2
```

```
w <- dirac (a-b > l)
```

====

```
a <- normal 10 3
```

```
b <- normal 10 3
```

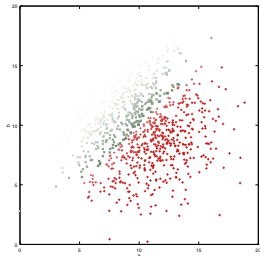
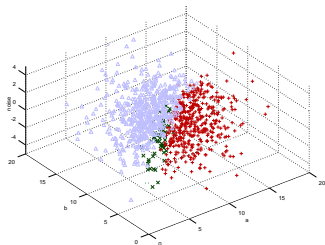
```
l <- normal 0 2
```

```
w <- counting
```

```
weight (if a-b > l then 1  
        else 0)
```

```
return (a > b)
```

```
return (a > b)
```



probability density (absolute continuity) w.r.t. counting

Continuous importance sampling revisited

```
x <- normal      10 3
```

```
m <- normal      x 1
```

```
x' <- normal (x+5) 2
```

```
...
```

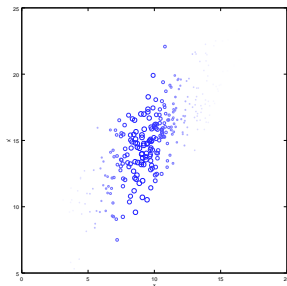
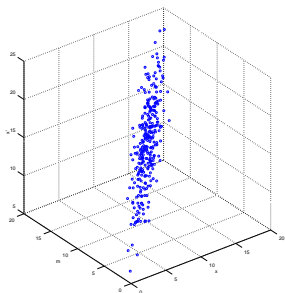
```
x <- normal      10 3
```

```
m <- lebesgue
```

== $\text{weight } e^{-(m-x)^2/2} / \sqrt{2\pi}$

```
x' <- normal (x+5) 2
```

```
...
```

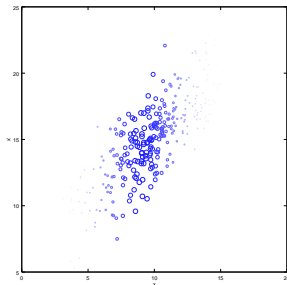
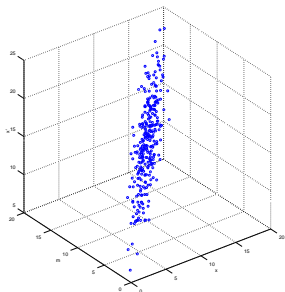


probability density (absolute continuity) w.r.t. lebesgue

Continuous importance sampling revisited

```
x <- normal      10 3  
m <- normal      x 1  
  
x' <- normal (x+5) 2  
...
```

```
↗ x <- normal      10 3  
  m <- lebesgue  
  == weight  $e^{-(m-x)^2/2}/\sqrt{2\pi}$   
x' <- normal (x+5) 2  
...
```

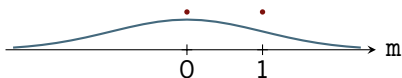


probability density (absolute continuity) w.r.t. lebesgue

Discrete+continuous importance sampling revisited

```
x <- flip True False
m <- (if x then flip 0 1 else normal 0 1)
...

||
x <- flip True False
m <- (x' <- flip True False
      if x' then flip 0 1 else normal 0 1)
weight (if x then if m==0 || m==1 then 2 else 0
        else if m==0 || m==1 then 0 else 2)
...
```

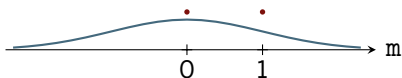


probability density (absolute continuity) w.r.t. marginal

Discrete+continuous importance sampling revisited

```
x <- flip True False  
m <- (if x then flip 0 1 else normal 0 1)  
...
```

```
||  
↑  
(x <- flip True False  
 m <- (x' <- flip True False  
       if x' then flip 0 1 else normal 0 1)  
weight (if x then if m==0 || m==1 then 2 else 0  
        else if m==0 || m==1 then 0 else 2)  
...)
```



probability density (absolute continuity) w.r.t. marginal

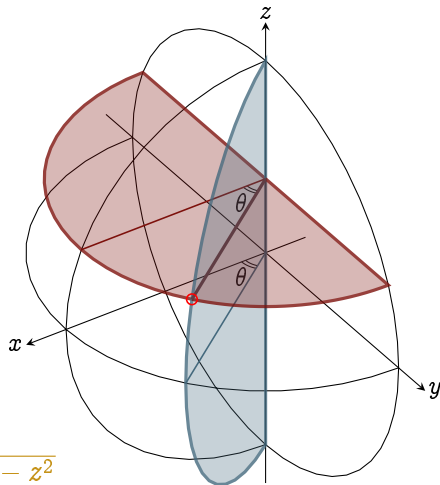
Borel's paradox

Requires change of variable:

```
z <- uniform  -1      1
θ <- uniform  -π/2   π/2
y <- dirac    √(1-z²) sin θ
...
```

||

```
z <- uniform  -1      1
y <- uniform  -√(1-z²) √(1-z²)
θ <- dirac    arcsin(y/√(1-z²))
weight 2/cos θ
...
```



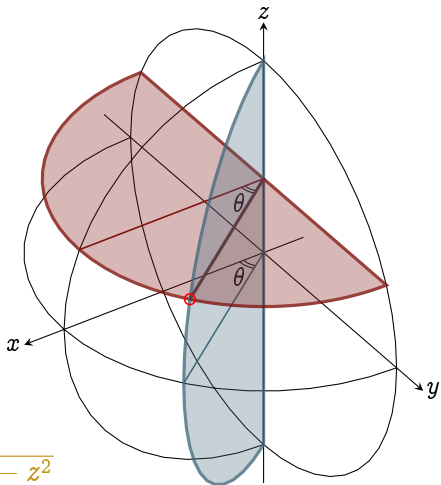
Borel's paradox

Requires change of variable:

$\left\{ \begin{array}{l} z \leftarrow \text{uniform} \quad -1 \quad 1 \\ \theta \leftarrow \text{uniform} \quad -\pi/2 \quad \pi/2 \\ y \leftarrow \text{dirac} \quad \sqrt{1-z^2} \sin \theta \\ \dots \end{array} \right.$

||

$\left\{ \begin{array}{l} z \leftarrow \text{uniform} \quad -1 \quad 1 \\ y \leftarrow \text{uniform} \quad -\sqrt{1-z^2} \quad \sqrt{1-z^2} \\ \theta \leftarrow \text{dirac} \quad \arcsin(y/\sqrt{1-z^2}) \\ \text{weight} \quad 2/\cos \theta \\ \dots \end{array} \right.$



Another desideratum

Generative story

```
x <- normal 0 1  
m <- dirac (x * 2)
```

Observed effect

```
condition (m = 32)
```

Hidden cause

```
return (x == 16)
```

Should give True with 100% probability.

Another desideratum

Generative story

```
x <- normal 0 1  
m <- dirac (x / 2)
```

Observed effect

```
condition (m = 32)
```

Hidden cause

```
return (x == 64)
```

Should give True with 100% probability.

Conditioning means disintegration.

(Chang & Pollard)

If the conditioned choice has a density with respect to an ambient measure, *then* we can transform the program locally into importance sampling.

- ▶ Simple ambient measures: counting, lebesgue
- ▶ Complex ambient measures: marginal, ...

How to infer an ambient measure?

How to calculate density with respect to it?

(Pfeffer, Bhat et al.)



Conditioning means disintegration.

(Chang & Pollard)

If the conditioned choice has a density with respect to an ambient measure, *then* we can transform the program locally into importance sampling.

- ▶ Simple ambient measures: counting, lebesgue
- ▶ Complex ambient measures: marginal, ...

How to infer an ambient measure?

How to calculate density with respect to it?

(Pfeffer, Bhat et al.)



Density calculator demo

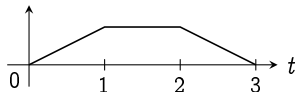
```
x <- uniform 0 1  
x + x + uniform 0 1
```

↓

$$\int_0^1 \langle 0 < t - x - x < 1 \rangle dx$$

↓

$$\begin{cases} 0 & \text{if } t < 0 \\ t/2 & \text{if } 0 \leq t < 1 \\ 1/2 & \text{if } 1 \leq t < 2 \\ 3/2 - t/2 & \text{if } 2 \leq t < 3 \\ 0 & \text{if } 3 \leq t \end{cases}$$



Density calculator demo

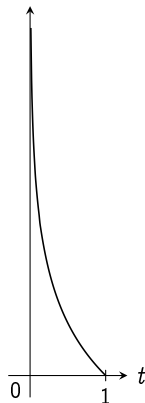
$$\exp (\log (\text{uniform } 0 \ 1) + \log (\text{uniform } 0 \ 1))$$

\Downarrow

$$\begin{cases} \int_0^1 \langle 0 < e^{\ln t - \ln x} < 1 \rangle e^{\ln t - \ln x} dx / t & \text{if } 0 < t \\ 0 & \text{otherwise} \end{cases}$$

\Downarrow

$$\begin{cases} -\ln t & \text{if } 0 < t < 1 \\ 0 & \text{otherwise} \end{cases}$$



Density calculator demo

```
x <- uniform 0 1  
(if x < .2 then 0 else uniform 0 1)  
  + (if x > .7 then 1 else uniform 0 1)
```

Pfeffer's approximate algorithm randomly samples from one term then calculates density of the other term.

Mochastic vs stochastic lambda calculus

Mochastic/stochastic only

```
x <- normal 0 1  
return (exp x + 1)
```

```
x <- normal 0 1  
y <- normal 0 1  
return (x + y)
```

```
x <- flip True False  
if x  
  then flip 0 1  
  else normal 0 1
```

```
x <- normal 0 1  
return (x + x)
```

Stochastic

```
exp (normal 0 1) + 1
```

```
normal 0 1 + normal 0 1
```

```
if flip True False  
  then flip 0 1  
  else normal 0 1
```

```
none
```


Stochastic lambda calculus: expectation

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Stochastic lambda calculus: density

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Goal: Given ε , find $D(\varepsilon)$ such that

$$\llbracket \varepsilon \rrbracket \rho \ c = \int D(\varepsilon) \rho \ t \times c(t) \, dt \quad \text{for all } \rho, c.$$

Approach: Define $D(\varepsilon)$ by recursion on ε .

Stochastic lambda calculus: density

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Goal: Given ε , find $D(\varepsilon)$ such that

$$\llbracket \varepsilon \rrbracket \rho \ c = \int D(\varepsilon) \rho \ t \times c(t) \, dt \quad \text{for all } \rho, c.$$

One base case:

$$D(\text{uniform } 0 \ 1) \rho \ t = \langle 0 < t < 1 \rangle$$

Stochastic lambda calculus: density

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Goal: Given ε , find $D(\varepsilon)$ such that

$$\llbracket \varepsilon \rrbracket \rho \ c = \int D(\varepsilon) \rho \ t \times c(t) \, dt \quad \text{for all } \rho, c.$$

One recursive case:

$$D(\text{exp } \varepsilon) \rho \ t = ???$$

$$\llbracket \text{exp } \varepsilon \rrbracket \rho \ c = \int_{-\infty}^{\infty} ??? \times c(t) \, dt$$

Stochastic lambda calculus: density

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Goal: Given ε , find $D(\varepsilon)$ such that

$$\llbracket \varepsilon \rrbracket \rho \ c = \int D(\varepsilon) \rho \ t \times c(t) \, dt \quad \text{for all } \rho, c.$$

One recursive case:

$$D(\text{exp } \varepsilon) \rho \ t = ???$$

$$\begin{aligned}\llbracket \text{exp } \varepsilon \rrbracket \rho \ c &= \int_{-\infty}^{\infty} ??? \times c(t) \, dt \\ \parallel \\ \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x)) &= \int_{-\infty}^{\infty} D(\varepsilon) \rho \ x \times c(e^x) \, dx\end{aligned}$$

Stochastic lambda calculus: density

$$\begin{aligned}\llbracket \text{uniform } 0 \ 1 \rrbracket \rho \ c &= \int_0^1 c(t) \, dt \\ \llbracket \exp \ \varepsilon \rrbracket \rho \ c &= \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x))\end{aligned}$$

Goal: Given ε , find $D(\varepsilon)$ such that

$$\llbracket \varepsilon \rrbracket \rho \ c = \int D(\varepsilon) \rho \ t \times c(t) \, dt \quad \text{for all } \rho, c.$$

One recursive case:

$$\begin{aligned}D(\exp \ \varepsilon) \rho \ t &= \langle t > 0 \rangle \frac{D(\varepsilon) \rho \ (\ln t)}{t} \\ \llbracket \exp \ \varepsilon \rrbracket \rho \ c &= \int_{-\infty}^{\infty} \langle t > 0 \rangle \frac{D(\varepsilon) \rho \ (\ln t)}{t} \times c(t) \, dt \\ &\quad \parallel \parallel \\ \llbracket \varepsilon \rrbracket \rho \ (\lambda x. c(e^x)) &= \int_{-\infty}^{\infty} D(\varepsilon) \rho \ x \times c(e^x) \, dx\end{aligned}$$

$$\begin{aligned}\llbracket \varepsilon_1 + \varepsilon_2 \rrbracket \rho c &= \llbracket \varepsilon_1 \rrbracket \rho (\lambda x_1. \llbracket \varepsilon_2 \rrbracket \rho (\lambda x_2. c(x_1 + x_2))) \\ &= \llbracket \varepsilon_2 \rrbracket \rho (\lambda x_2. \llbracket \varepsilon_1 \rrbracket \rho (\lambda x_1. c(x_1 + x_2)))\end{aligned}$$

Randomized algorithm for binary operators

$$\begin{aligned}D(\varepsilon_1 + \varepsilon_2) \rho t &= \llbracket \varepsilon_1 \rrbracket \rho (\lambda x. D(\varepsilon_2) \rho (t - x)) \\ &= \llbracket \varepsilon_2 \rrbracket \rho (\lambda x. D(\varepsilon_1) \rho (t - x))\end{aligned}$$

$$\llbracket 42 \rrbracket \rho c = c(42)$$

$$\llbracket \text{var} \rrbracket \rho c = c(\rho \text{ var})$$

$$\llbracket \text{var} \leftarrow \varepsilon_1; \varepsilon_2 \rrbracket \rho c = \llbracket \varepsilon_1 \rrbracket \rho (\lambda x. \llbracket \varepsilon_2 \rrbracket (\rho\{\text{var} \mapsto x\}) c)$$

Three strategies for bound variables

$$D(\text{bool_var}) \rho t = \langle \rho \text{ bool_var} = t \rangle$$

$$D(\text{var} \leftarrow \varepsilon_1; \varepsilon_2) \rho t = D(\varepsilon_2\{\text{var} \mapsto \varepsilon_1\}) \rho t$$

if ε_2 uses var at most once

$$D(\text{var} \leftarrow \varepsilon_1; \varepsilon_2) \rho t = \llbracket \varepsilon_1 \rrbracket \rho (\lambda x. D(\varepsilon_2) (\rho\{\text{var} \mapsto x\}) (t))$$

Summary

Probabilistic programming

- ▶ Denote measure by generative story
- ▶ Run backwards to infer cause from effect

Mathematical reasoning

- ▶ Define conditioning as disintegration
- ▶ Perform importance sampling
- ▶ Derive density calculator

Need semantics and inference for loops

- ▶ Bag of words
- ▶ Brownian motion
- ▶ Probabilistic context-free grammars



Come to Indiana University to create essential abstractions and practical languages for clear, robust and efficient programs.



Dan Friedman

relational & logic languages,
meta-circularity & reflection



Ryan Newton

streaming, distributed & GPU DSLs,
Haskell deterministic parallelism



Amr Sabry

quantum computing, type
theory, information effects



Chung-chieh Shan

probabilistic programming,
semantics



Jeremy Siek

gradual typing,
mechanized metatheory,
high performance



Sam Tobin-Hochstadt

types for untyped languages,
contracts,
languages for the Web

Check out our work: Boost Libraries · Build to Order BLAS · C++ Concepts · Chapel Generics · HANSEI · JavaScript Modules · Racket & Typed Racket · miniKanren · LVars · monad-par · meta-par · WaveScript

<http://lambda.soic.indiana.edu/>