



Symbolic disintegration with a variety of base measures

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Exact calculation

for approximate computation

Exact calculation

for approximate computation

Automatic differentiation

for gradient descent

Automatic disintegration

for inference and sampling

Exact calculation

for approximate computation

Automatic differentiation

for gradient descent

Automatic disintegration

for inference and sampling

A variety of base measures

Disintegration

$$(t, p) \rightsquigarrow \mu = \begin{array}{l} t \rightsquigarrow \beta \\ p \rightsquigarrow \kappa(t) \end{array} : \mathbb{M}(T \times P)$$

Disintegration relates a joint measure
 $\mu : \mathbb{M}(T \times P)$

$$(t, p) \sim \mu = t \sim \beta \quad : \mathbb{M}(T \times P)$$
$$p \sim \kappa(t)$$

Disintegration relates a joint measure with a base measure

$$\mu : \mathbb{M}(T \times P)$$

$$\beta : \mathbb{M} T$$

$$(t, p) \sim \mu$$

$$= t \sim \beta$$

$$p \sim \kappa(t)$$

$$: \mathbb{M}(T \times P)$$

Disintegration relates a joint measure with a base measure and a kernel

$\mu : \mathbb{M}(T \times P)$

$\beta : \mathbb{M} T$

$\kappa : T \rightarrow \mathbb{M} P$

by the equation

$$(t, p) \sim \mu = t \sim \beta$$
$$p \sim \kappa(t) : \mathbb{M}(T \times P)$$

The diagram illustrates the components of disintegration. It features three light brown rectangular boxes at the top. The first box contains the text 'Disintegration relates' followed by 'a joint measure' and the mathematical expression ' $\mu : \mathbb{M}(T \times P)$ '. The second box contains the text 'with' followed by 'a base measure' and the mathematical expression ' $\beta : \mathbb{M} T$ '. The third box contains the text 'and' followed by 'a kernel' and the mathematical expression ' $\kappa : T \rightarrow \mathbb{M} P$ '. Below these boxes, the text 'by the equation' is followed by two equations: ' $(t, p) \sim \mu$ ' and ' $= t \sim \beta$ ' on the left, and ' $p \sim \kappa(t)$ ' and ' $: \mathbb{M}(T \times P)$ ' on the right. Three yellow arrows point from the bottom of each box to the corresponding part of the equations below.

Disintegration relates a joint measure with a base measure and a kernel

$\mu : \mathbb{M}(T \times P)$

$\beta : \mathbb{M} T$

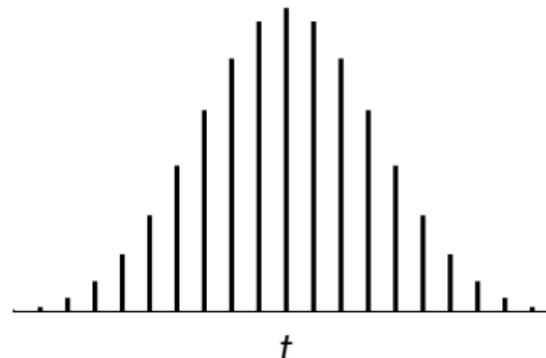
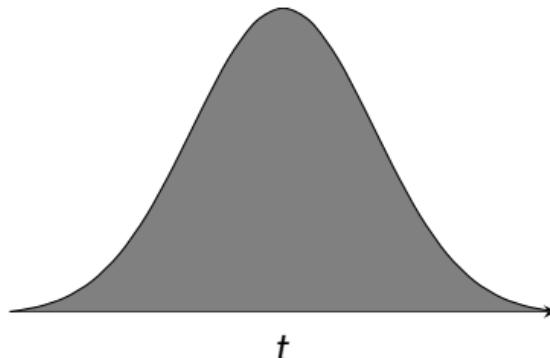
$\kappa : T \rightarrow \mathbb{M} P$

by the equation

$$(t, p) \sim \mu = t \sim \beta \\ p \sim \kappa(t) : \mathbb{M}(T \times P)$$

Generalizes density:

$$t \sim \text{normal} = t \sim \text{lebesgue} : \mathbb{M}(\mathbb{R} \times \mathbb{1})$$
$$p = () \quad p \sim \text{factor}(\text{dnorm } t)$$



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Generalizes conditioning:

$$x \sim \text{normal} = t \sim \text{lebesgue} : \mathbb{M}(\mathbb{R} \times \mathbb{R}^2)$$

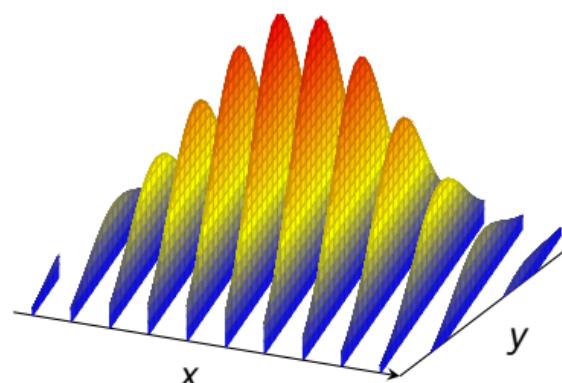
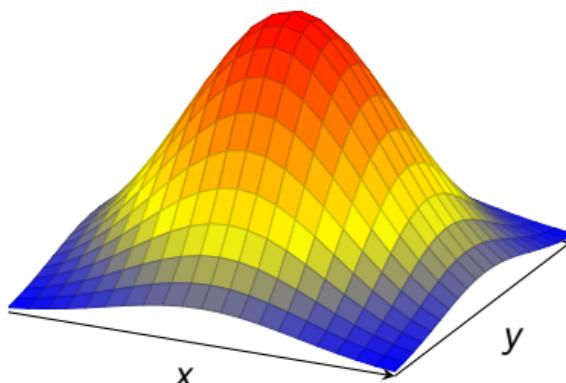
$$y \sim \text{normal}$$

$$p \sim \dots \Pr(p, t) \dots$$

$$t \sim 5 \cdot x + 0.1 \cdot y$$

$$p = (x, y)$$

“unnormalized conditioning”



Disintegration relates a joint measure with a base measure and a kernel

$$\mu : \mathbb{M}(T \times P)$$

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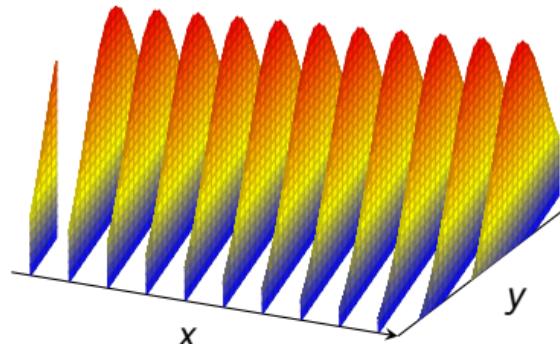
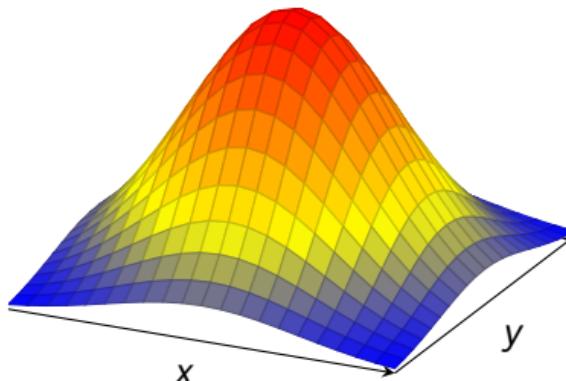
$$\kappa : T \rightarrow \mathbb{M} P$$

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Generalizes conditioning:

$x \sim \text{normal}$	$= t \sim \dots \Pr(t) \dots$	$: \mathbb{M}(\mathbb{R} \times \mathbb{R}^2)$
$y \sim \text{normal}$	$p \sim \dots \Pr(p t) \dots$	
$t \sim 5 \cdot x + 0.1 \cdot y$		
$p = (x, y)$		



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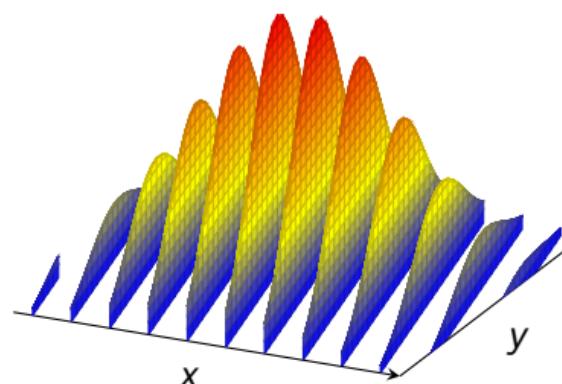
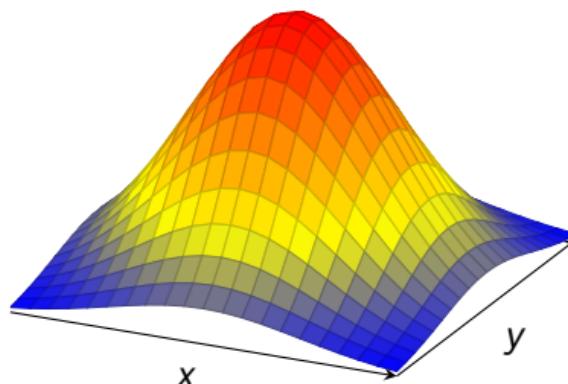
$$\kappa : T \rightarrow \mathbb{M} P$$

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Generalizes conditioning:

$x \sim \text{normal}$	$=$	$t \sim \text{lebesgue}$	$: \mathbb{M}(\mathbb{R} \times \mathbb{R}^2)$
$y \sim \text{normal}$		$p \sim \dots \Pr(p, t) \dots$	
$t \sim 5 \cdot x + 0.1 \cdot y$			
$p = (x, y)$			"unnormalized conditioning"



Disintegration relates a joint measure with a base measure and a kernel

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Generalizes density and conditioning

Can be thought of as unnormalized conditioning

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A semantics-preserving transformation on probabilistic programs

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random choice (**normal**),
scoring (**factor**)

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sequence of operations,
not just a primitive

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s-finite measures/kernels

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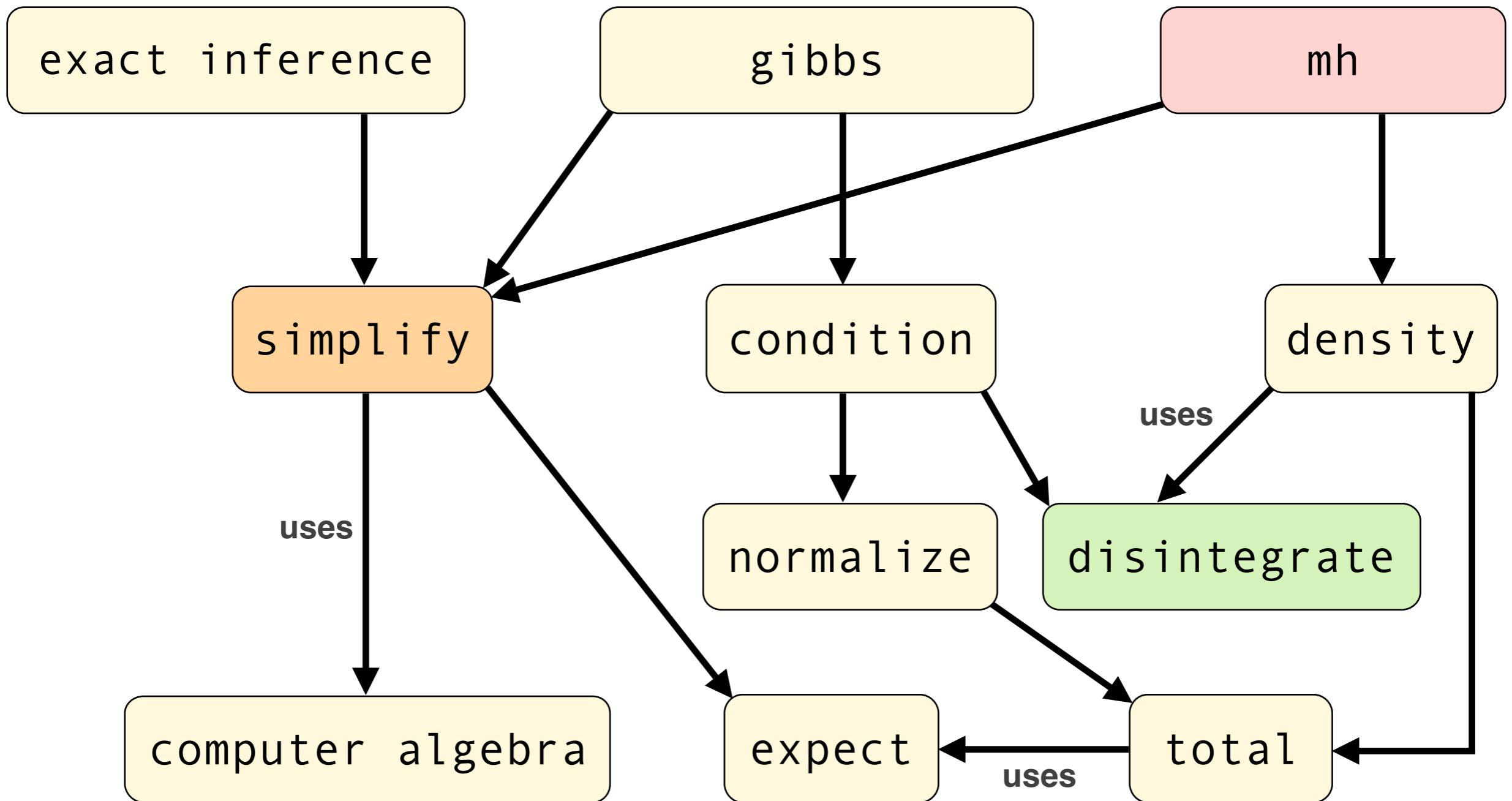
sequence of operations,
not just a primitive

Derived by equational reasoning (hence proven sound by construction)

= This talk: equational reasoning on example programs

+ Established PL technology: lazy and partial evaluation (traversing computation graph)

Composable transformations



Modeling

Conditioning

Optimizing

Sampling

```
model = ... `bind` \... →  
    ...  
    dirac (pair ... )
```

disintegrate

```
lam $ \... →  
    ...  
    dirac ...
```

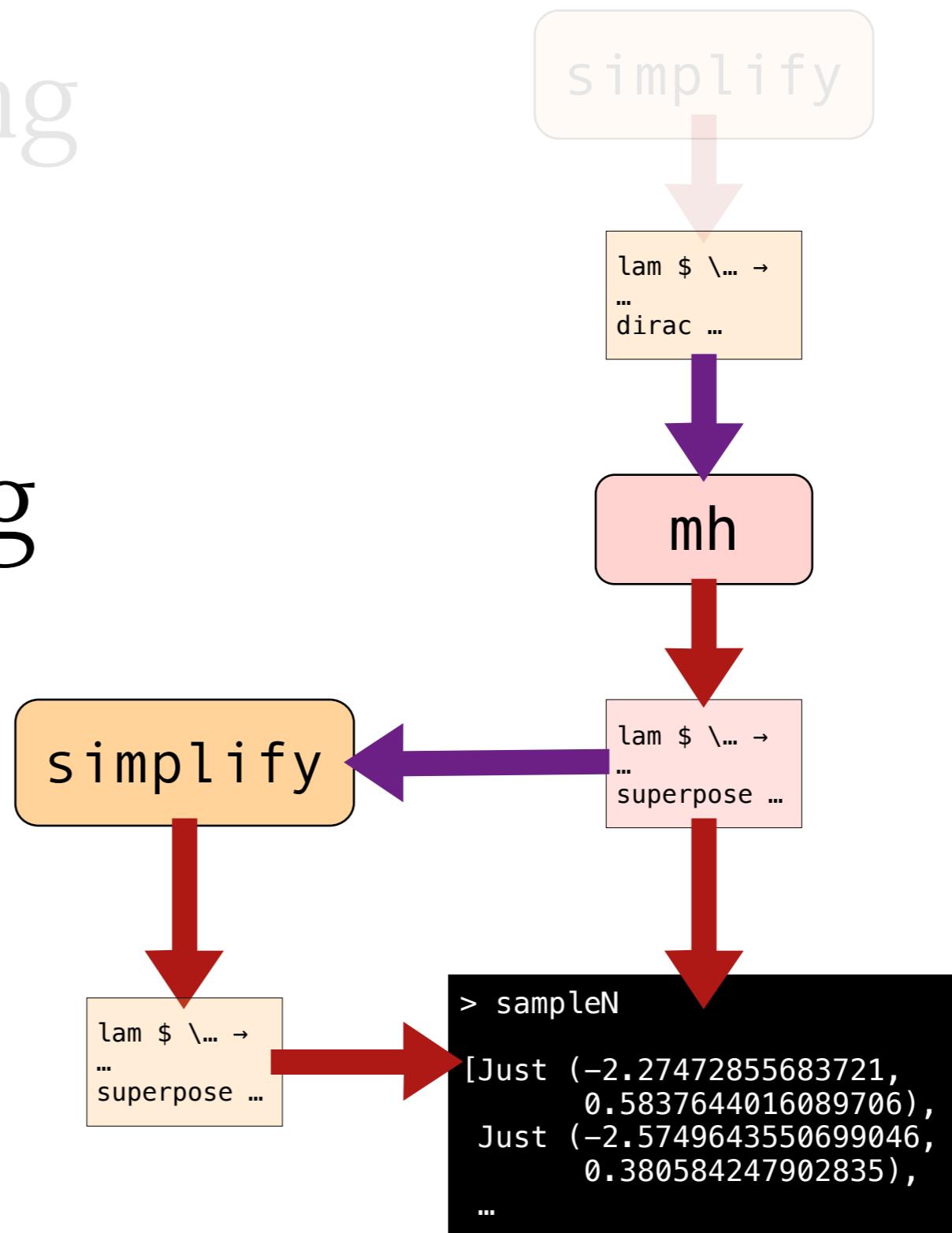
simplify

```
lam $ \... →  
    ...  
    dirac ...
```

```
> sampleN  
[Just (-2.27472855683721,  
       0.5837644016089706),  
 Just (-2.5749643550699046,  
       0.380584247902835),  
 ...]
```

Optimizing

Sampling



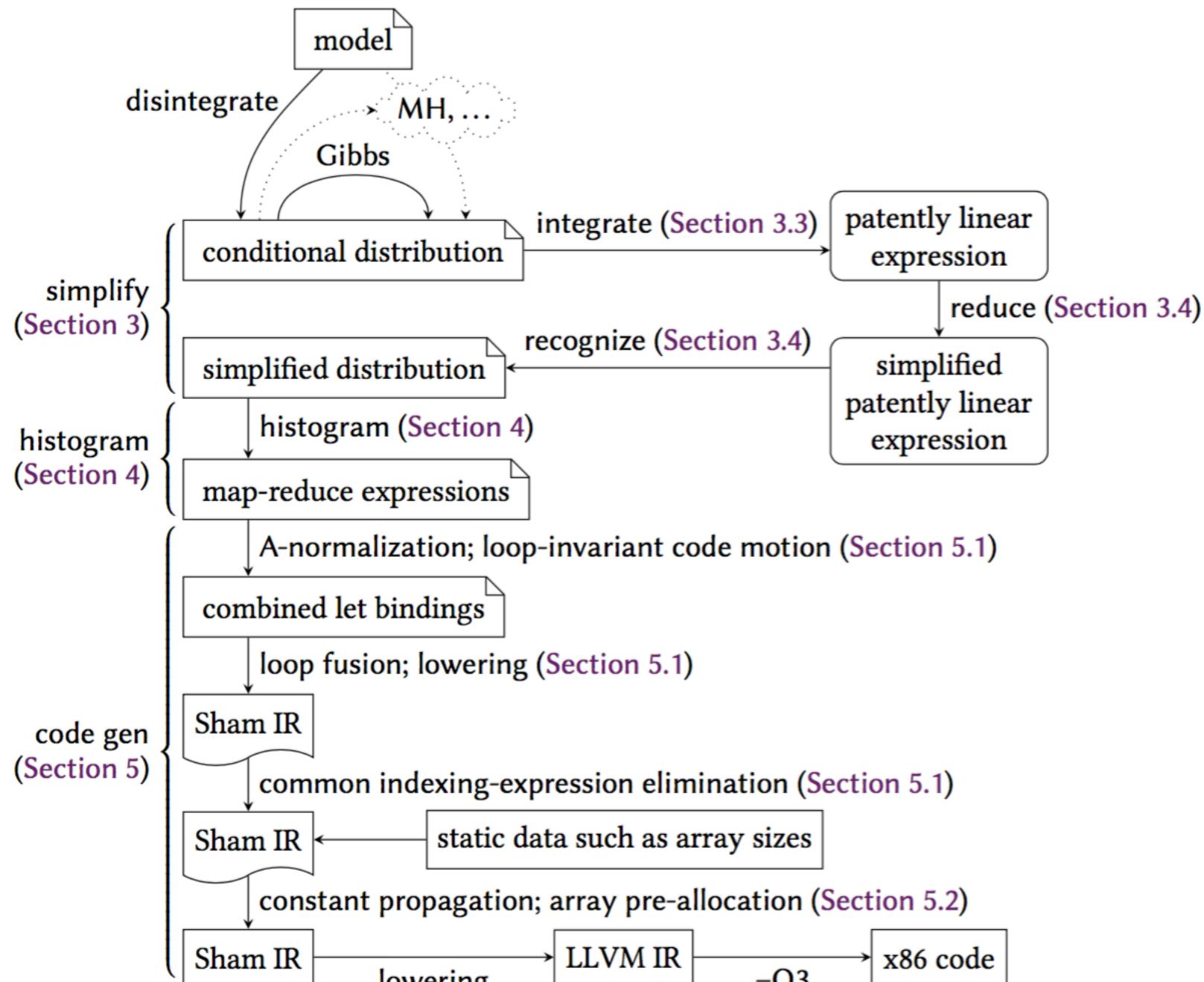


Fig. 1. Our pipeline, compiling **probabilistic** programs via **math** into **imperative** code to process **data**

A growing variety of base measures

Bhat et al. POPL 2012,
Shan & Ramsey POPL 2017

$\beta ::= \text{lebesgue}$
| counting
| $\beta \otimes \beta$

A growing variety of base measures

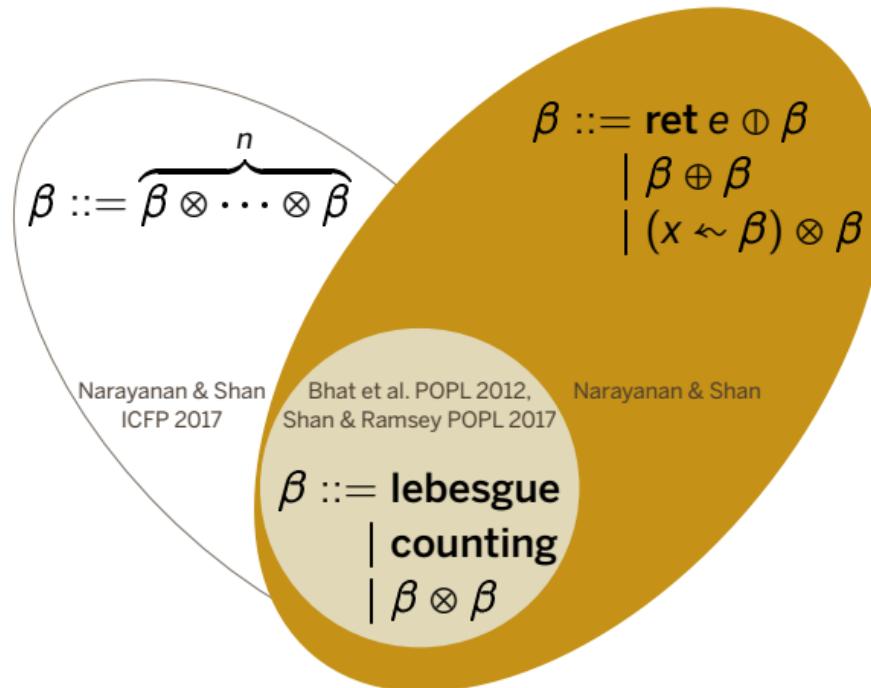
$$\beta ::= \overbrace{\beta \otimes \cdots \otimes \beta}^n$$

Narayanan & Shan
ICFP 2017

Bhat et al. POPL 2012,
Shan & Ramsey POPL 2017

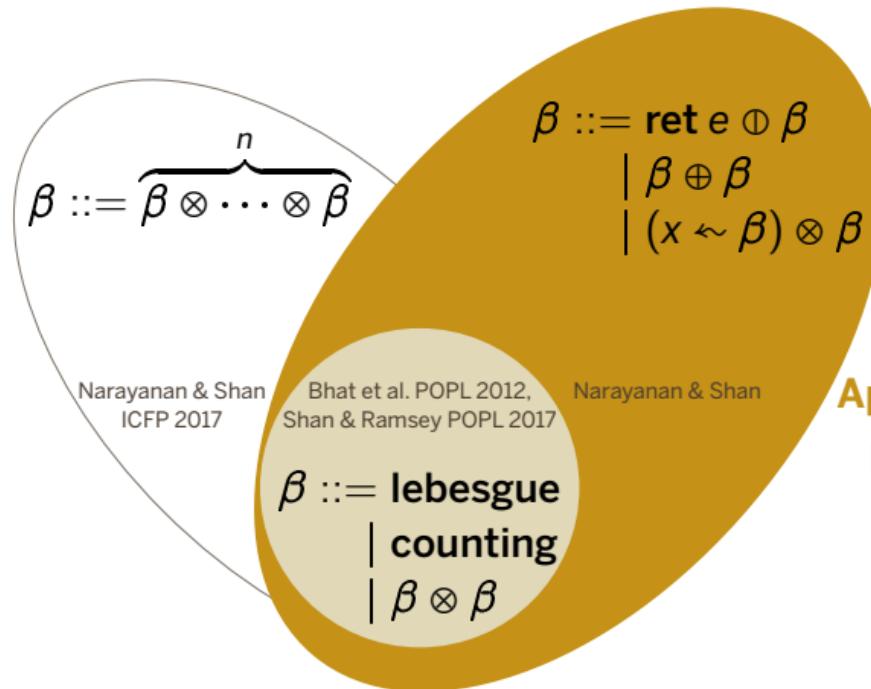
$$\beta ::= \begin{array}{l} \text{lebesgue} \\ | \text{counting} \\ | \beta \otimes \beta \end{array}$$

A growing variety of base measures



Discrete-continuous mixtures
Disjoint sums
Dependent products

A growing variety of base measures

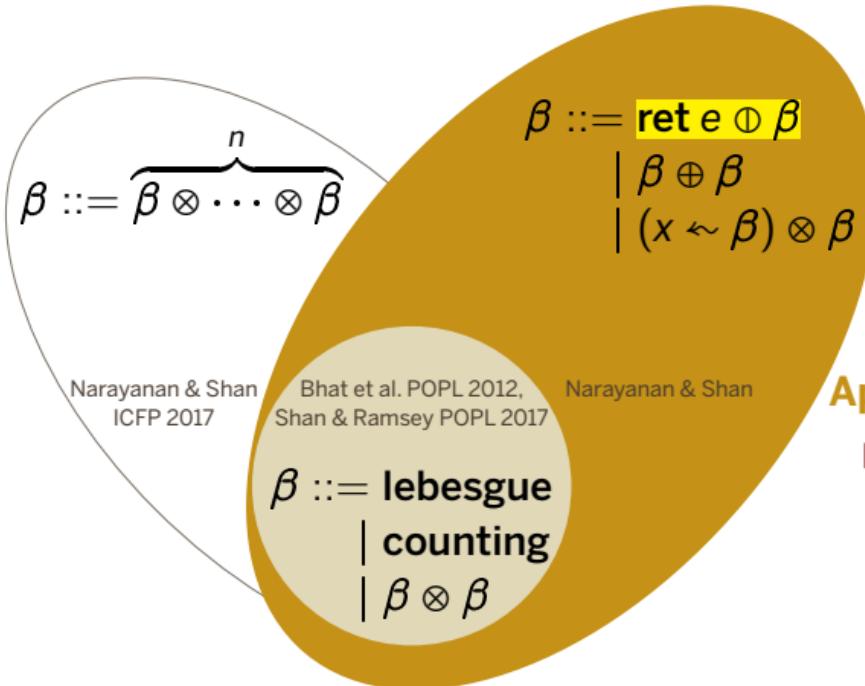


Discrete-continuous mixtures
Disjoint sums
Dependent products

Applications:

- ▶ clamped model/observation (GPA, Tobit, camera)
 - ▶ likelihood ratio, importance sampling, mutual information
 - ▶ belief update, Gibbs sampling
- ▶ Metropolis-Hastings sampling
 - ▶ single site
 - ▶ reversible jump, light transport

A growing variety of base measures



Discrete-continuous mixtures

Disjoint sums

Dependent products

To appear in TOPLAS

Applications:

- ▶ clamped model/observation
(GPA, Tobit, camera)
 - ▶ likelihood ratio, importance sampling, mutual information
 - ▶ belief update, Gibbs sampling
- ▶ Metropolis-Hastings sampling
 - ▶ single site
 - ▶ reversible jump, light transport

Fixed-base disintegration

$x \sim \text{normal}$

$y \sim \text{normal}$

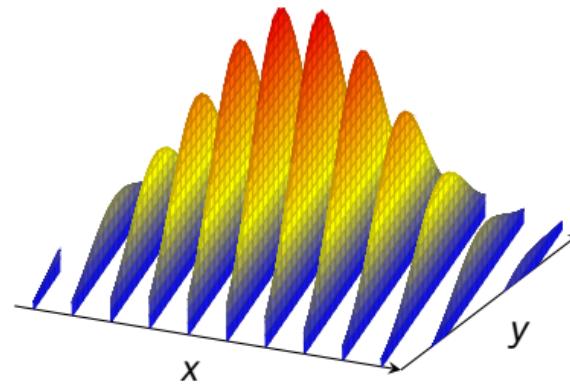
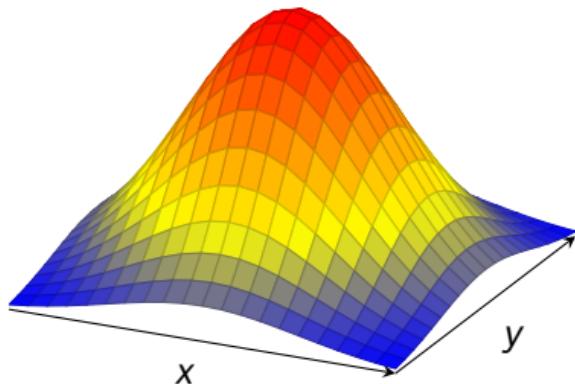
$$t = 5 \cdot x + 0.1 \cdot y$$

$$p = (x, y)$$

=

$t \sim \text{lebesgue}$

$p \sim ???$



Fixed-base disintegration

$x \sim \text{normal}$

$y \sim \text{normal}$

$$t = 5 \cdot x + 0.1 \cdot y$$

$$p = (x, y)$$

=

$x \sim \text{normal}$

$y \sim \text{lebesgue}$

$$t = 5 \cdot x + 0.1 \cdot y$$

factor (dnorm y)

$$p = (x, y)$$

=

$t \sim \text{lebesgue}$

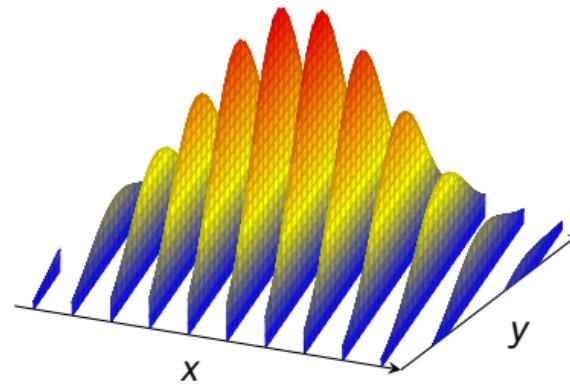
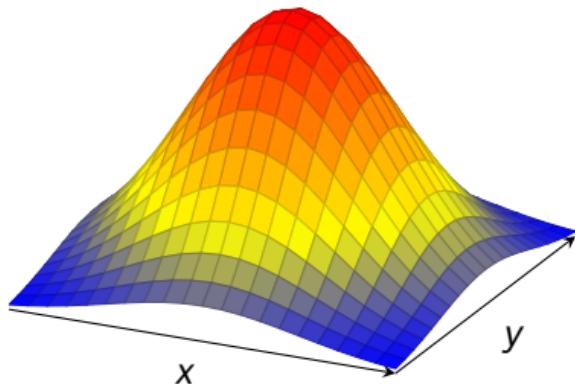
$x \sim \text{normal}$

$$y = 10 \cdot (t - 5 \cdot x)$$

factor 10

factor (dnorm y)

$$p = (x, y)$$



Fixed-base disintegration

$x \sim \text{normal}$

$y \sim \text{normal}$

$$t = 5 \cdot x + 0.1 \cdot y$$

$$p = (x, y)$$

density

$x \sim \text{normal}$

$y \sim \text{lebesgue}$

$$t = 5 \cdot x + 0.1 \cdot y$$

factor (dnorm y)

$$p = (x, y)$$

reparameterize

$t \sim \text{lebesgue}$

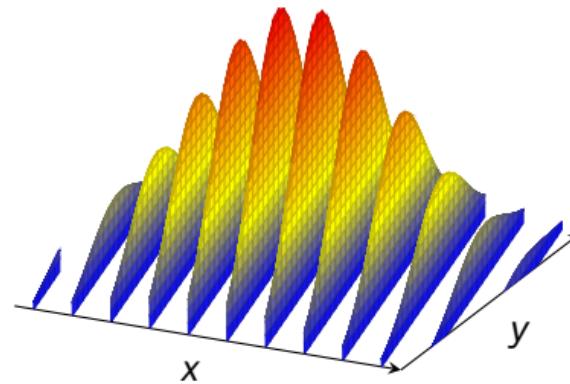
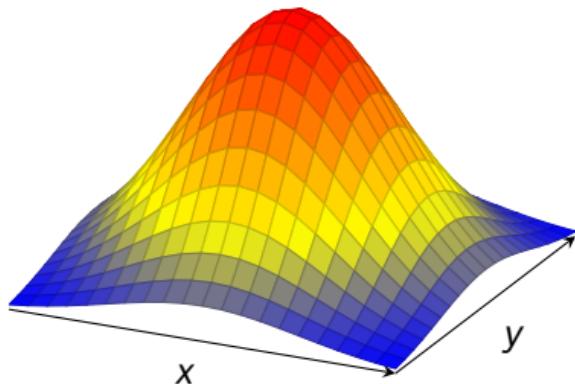
$x \sim \text{normal}$

$$y = 10 \cdot (t - 5 \cdot x)$$

factor 10

factor (dnorm y)

$$p = (x, y)$$



```

do {a ~ normal  $\mu_a \sigma_a$ ;  

b ~ normal  $\mu_b \sigma_b$ ;  

 $y_1$  ~ normal  $(a \cdot n_1 + b) 1$ ;  

 $y_2$  ~ normal  $(a \cdot n_2 + b) 1$ ;  

return  $((y_1, y_2), (a, b))\}$ 

```

$\lambda(t_1, t_2) \rightarrow$

```

do { $\triangleleft (\bar{y}_1, \bar{y}_2)$  ( $t_1, t_2$ ) [ $\bar{a} \sim \text{normal } \mu_a \sigma_a$ ;  

 $\bar{b} \sim \text{normal } \mu_b \sigma_b$ ;  

 $\bar{y}_1 \sim \text{normal } (a \cdot n_1 + b) 1$ ;  

 $\bar{y}_2 \sim \text{normal } (a \cdot n_2 + b) 1$ ];  

return  $(a, b)\}$ 

```

$\lambda(t_1, t_2) \rightarrow$

```

do { $\triangleleft \bar{y}_1 t_1$  [ $\bar{a} \sim \text{normal } \mu_a \sigma_a$ ;  

 $\bar{b} \sim \text{normal } \mu_b \sigma_b$ ;  

 $\bar{y}_1 \sim \text{normal } (a \cdot n_1 + b) 1$ ];  

 $\triangleleft \bar{y}_2 t_2 \dots$ ;  

return  $(a, b)\}$ 

```

$\lambda(t_1, t_2) \rightarrow$

```

do { $\triangleleft \bar{y}_2 t_2$  [ $\bar{a} \sim \text{normal } \mu_a \sigma_a$ ;  

 $\bar{b} \sim \text{normal } \mu_b \sigma_b$ ;  

factor (dNorm  $(a \cdot n_1 + b) 1 t_1$ );  

 $\bar{y}_2 \sim \text{normal } (a \cdot n_2 + b) 1$ ];  

return  $(a, b)\}$ 

```

$\lambda(t_1, t_2) \rightarrow$

```

do { $\bar{a} \sim \text{normal } \mu_a \sigma_a$ ;  

 $\bar{b} \sim \text{normal } \mu_b \sigma_b$ ;  

factor (dNorm  $(a \cdot n_1 + b) 1 t_1$ );  

factor (dNorm  $(a \cdot n_2 + b) 1 t_2$ );  

return  $(a, b)\}$ 

```

$\lambda(t_1, t_2) \rightarrow$

```

do {a ~ normal  $\mu_a \sigma_a$ ;  

b ~ normal  $\mu_b \sigma_b$ ;  

factor (dNorm  $(a \cdot n_1 + b) 1 t_1$ );  

factor (dNorm  $(a \cdot n_2 + b) 1 t_2$ );  

return  $(a, b)\}$ 

```

Disintegration for two measurements

```

do {a ~ normal  $\mu_a$   $\sigma_a$ ;  

   b ~ normal  $\mu_b$   $\sigma_b$ ;  

   y1 ~ normal (a •  $n_1$  + b) 1;  

   y2 ~ normal (a •  $n_2$  + b) 1;  

return ((y1, y2), (a, b))}
```

Line
 $M((\mathbb{R} \times \mathbb{R}) \times (\mathbb{R} \times \mathbb{R}))$

Measurements

$\lambda(t_1, t_2) \rightarrow$
do { $\triangleleft(\bar{y}_1, \bar{y}_2)(t_1, t_2)$ [**\bar{a}** ~ normal μ_a σ_a ;
 \bar{b} ~ normal μ_b σ_b ;
 \bar{y} ₁ ~ normal (**\bar{a}** • n_1 + **\bar{b}**) 1;
 \bar{y} ₂ ~ normal (**\bar{a}** • n_2 + **\bar{b}**) 1]
return (**\bar{a}** , **\bar{b}**)}

Observation

$(\mathbb{R} \times \mathbb{R}) \rightarrow M(\mathbb{R} \times \mathbb{R})$

Line

```

do { $a \leftarrow \text{normal } \mu_a \sigma_a;$ 
    $b \leftarrow \text{normal } \mu_b \sigma_b;$ 
    $y_1 \leftarrow \text{normal } (a \cdot n_1 + b) 1;$ 
    $y_2 \leftarrow \text{normal } (a \cdot n_2 + b) 1;$ 
return  $((y_1, y_2), (a, b))\}$ 
```

Constrain the measurements

to be the observation

$\lambda(t_1, t_2) \rightarrow$

```

do { $\triangleleft (\bar{y}_1, \bar{y}_2) (t_1, t_2)$   $\left[ \begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \leftarrow \text{normal } (\bar{a} \cdot n_1 + \bar{b}) 1; \\ \bar{y}_2 \leftarrow \text{normal } (\bar{a} \cdot n_2 + \bar{b}) 1 \end{array} \right];$ 
return  $(a, b)\}$ 
```

in the context
of the *heap*

$\lambda(t_1, t_2) \rightarrow$
 do { $\triangleleft(\bar{y}_1, \bar{y}_2)(t_1, t_2)$ $\left[\begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \leftarrow \text{normal } (a \cdot n_1 + b) 1; \\ \bar{y}_2 \leftarrow \text{normal } (a \cdot n_2 + b) 1 \end{array} \right];$
 return (a, b) }

Constrain is defined for each construct

$\lambda(t_1, t_2) \rightarrow$
 do { $\triangleleft \bar{y}_1 t_1$ $\left[\begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \leftarrow \text{normal } (a \cdot n_1 + b) 1; \\ \bar{y}_2 \leftarrow \text{normal } (a \cdot n_2 + b) 1 \end{array} \right];$
 $\triangleleft \bar{y}_2 t_2 \dots;$
 return (a, b) }

$\triangleleft e t h =$
 case e of
 $(e + e') \rightarrow \dots$
 $(e, e') \rightarrow \dots$
 \dots

Two recursive calls to **constrain**

```
 $\lambda(t_1, t_2) \rightarrow$ 
do {  $\triangleleft \bar{y}_1 t_1$   $\left[ \begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \leftarrow \text{normal } (a \cdot n_1 + b) 1; \\ \bar{y}_2 \leftarrow \text{normal } (a \cdot n_2 + b) 1 \end{array} \right];$ 
 $\triangleleft \bar{y}_2 t_2 ...;$ 
return (a, b)}
```

Replace binding
with
normal density

```
 $\lambda(t_1, t_2) \rightarrow$ 
do {  $\triangleleft \bar{y}_2 t_2$   $\left[ \begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \text{factor } (\text{dNorm } (a \cdot n_1 + b) 1 t_1); \\ \bar{y}_2 \leftarrow \text{normal } (a \cdot n_2 + b) 1 \end{array} \right];$ 
return (a, b)}
```

```
 $\lambda(t_1, t_2) \rightarrow$ 
do { <  $\bar{y}_2$   $t_2$   $\left[ \begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \text{factor (dNorm (a} \cdot n_1 + b) 1 t_1); \\ \bar{y}_2 \leftarrow \text{normal (a} \cdot n_2 + b) 1 \end{array} \right];$ 
    return (a, b)}
```

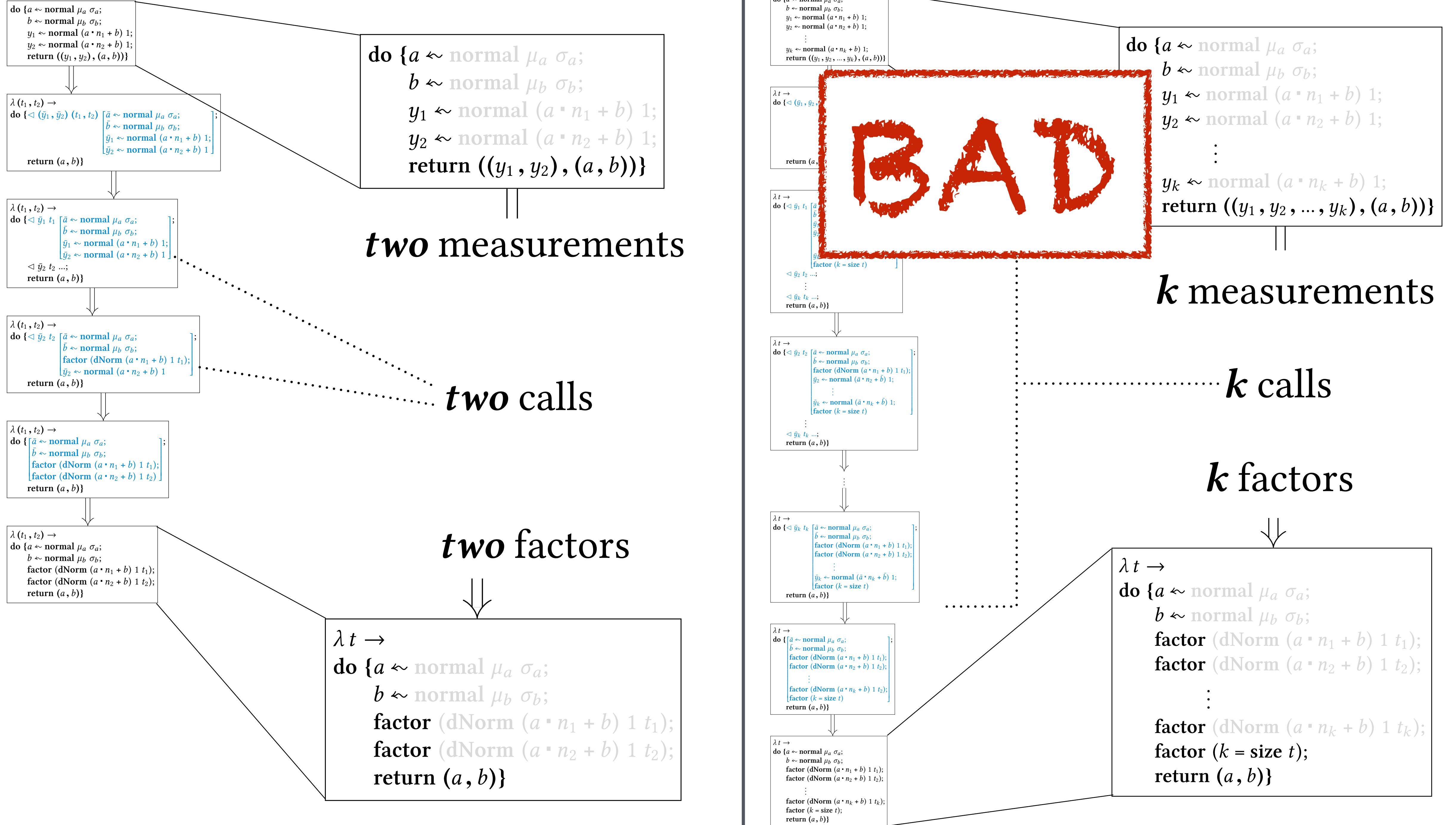
```
 $\lambda(t_1, t_2) \rightarrow$ 
do {  $\left[ \begin{array}{l} \bar{a} \leftarrow \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow \text{normal } \mu_b \sigma_b; \\ \text{factor (dNorm (a} \cdot n_1 + b) 1 t_1); \\ \text{factor (dNorm (a} \cdot n_2 + b) 1 t_2) \end{array} \right];$ 
    return (a, b)}
```

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with
normal density

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 $\lambda(t_1, t_2) \rightarrow$ 
do {  $\bar{a} \leftarrow \text{normal } \mu_a \sigma_a;$ 
       $\bar{b} \leftarrow \text{normal } \mu_b \sigma_b;$ 
      factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );
      factor (dNorm ( $a \cdot n_2 + b$ ) 1  $t_2$ )
    return ( $a, b$ )}
```

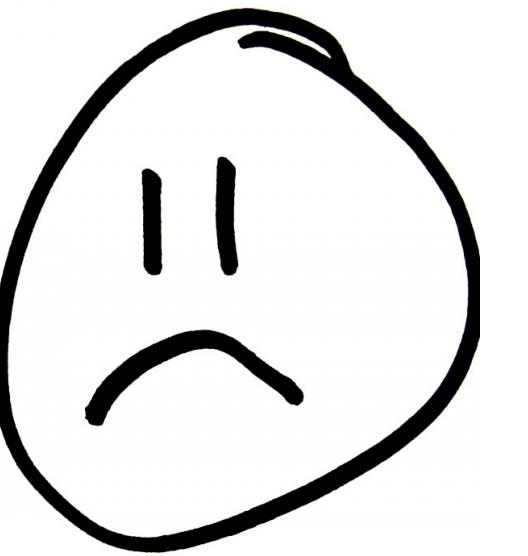
```
 $\lambda(t_1, t_2) \rightarrow$ 
do {  $a \leftarrow \text{normal } \mu_a \sigma_a;$ 
       $b \leftarrow \text{normal } \mu_b \sigma_b;$ 
      factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );
      factor (dNorm ( $a \cdot n_2 + b$ ) 1  $t_2$ );
    return ( $a, b$ )}
```

Absorb heap
into
final output

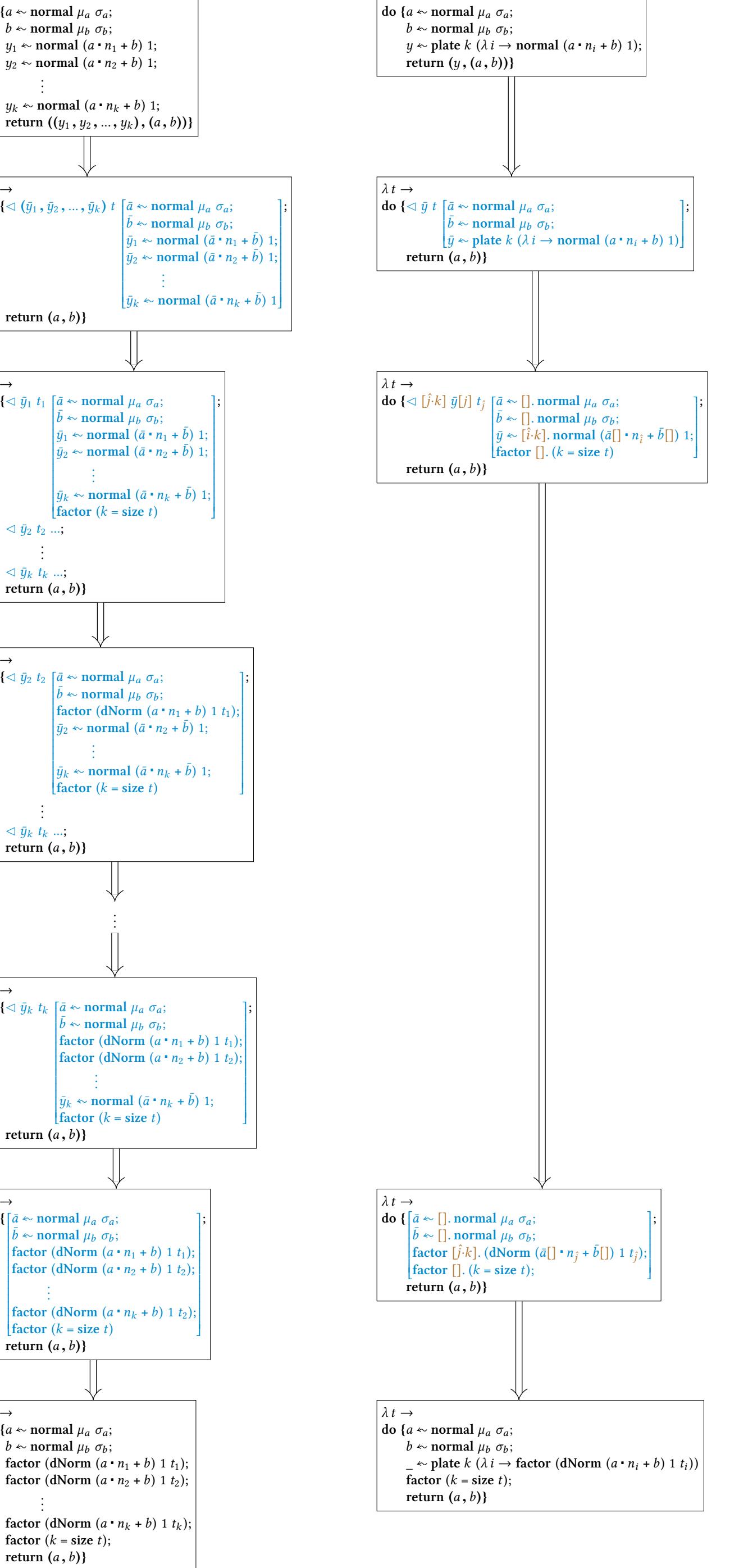


Unrolled

k calls

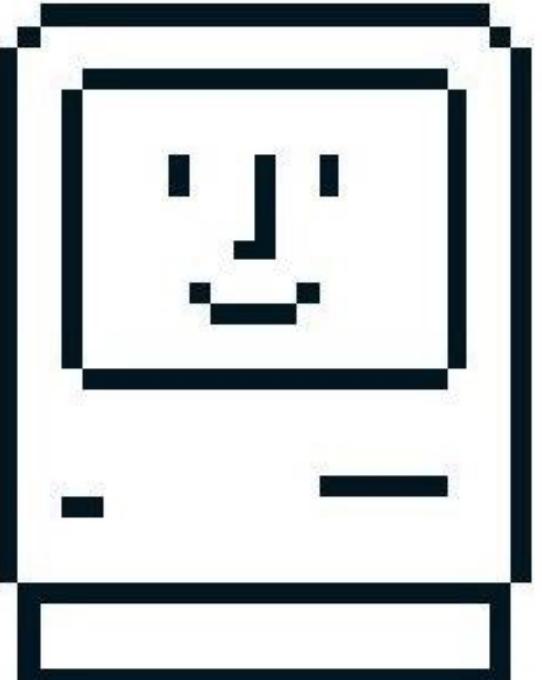
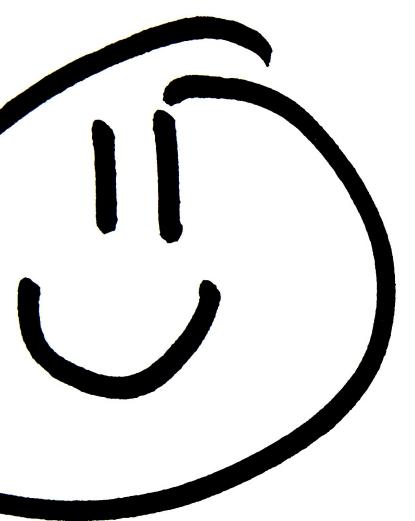


k factors



Lifted

one call



one factor

Unrolled

```
do {  
    a ~ normal  $\mu_a \sigma_a$ ;  
    b ~ normal  $\mu_b \sigma_b$ ;  
     $y_1 \sim \text{normal}(a \cdot n_1 + b) 1$ ;  
     $y_2 \sim \text{normal}(a \cdot n_2 + b) 1$ ;  
    ...  
     $y_k \sim \text{normal}(a \cdot n_k + b) 1$ ;  
    return  $((y_1, y_2, \dots, y_k), (a, b))$ };
```

become

Lifted

```
do {  
    a ~ normal  $\mu_a \sigma_a$ ;  
    b ~ normal  $\mu_b \sigma_b$ ;  
     $y \sim \text{plate } k (\lambda i \rightarrow \text{normal}(a \cdot n_i + b) 1)$ ;  
    return  $(y, (a, b))$ };
```

array

k-tuple

$\lambda t \rightarrow$
do { $\triangleleft (\bar{y}_1, \bar{y}_2, \dots, \bar{y}_k) t$ [$\bar{a} \sim \text{normal } \mu_a \sigma_a$;
 $\bar{b} \sim \text{normal } \mu_b \sigma_b$;
 $\bar{y}_1 \sim \text{normal}(\bar{a} \cdot n_1 + \bar{b}) 1$;
 $\bar{y}_2 \sim \text{normal}(\bar{a} \cdot n_2 + \bar{b}) 1$;
...
 $\bar{y}_k \sim \text{normal}(\bar{a} \cdot n_k + \bar{b}) 1$]
size
return (a, b) }

indexed dist.

$\lambda t \rightarrow$
do { $\triangleleft \bar{y} t$ [$\bar{a} \sim \text{normal } \mu_a \sigma_a$;
 $\bar{b} \sim \text{normal } \mu_b \sigma_b$;
 $\bar{y} \sim \text{plate } k (\lambda i \rightarrow \text{normal}(a \cdot n_i + b) 1)$;
return (a, b) }
dist. over arrays

Unrolled

```
do {  
    a ~ normal  $\mu_a$   $\sigma_a$ ;  
    b ~ normal  $\mu_b$   $\sigma_b$ ;  
    y1 ~ normal (a ·  $n_1$  + b) 1;  
    y2 ~ normal (a ·  $n_2$  + b) 1;  
      
    :  
      
    yk ~ normal (a ·  $n_k$  + b) 1;  
    return ((y1, y2, ..., yk), (a, b))}
```

Lifted

```
do {  
    a ~ normal  $\mu_a$   $\sigma_a$ ;  
    b ~ normal  $\mu_b$   $\sigma_b$ ;  
    y ~ plate  $k$  ( $\lambda i \rightarrow$  normal (a ·  $n_i$  + b) 1);  
    return (y, (a, b))}
```



$\lambda t \rightarrow$

do { $\triangleleft (\bar{y}_1, \bar{y}_2, \dots, \bar{y}_k) t$ [$\bar{a} \sim \text{normal } \mu_a \sigma_a$;
 $\bar{b} \sim \text{normal } \mu_b \sigma_b$;
 $\bar{y}_1 \sim \text{normal } (\bar{a} \cdot n_1 + \bar{b}) 1$;
 $\bar{y}_2 \sim \text{normal } (\bar{a} \cdot n_2 + \bar{b}) 1$;
 :
 $\bar{y}_k \sim \text{normal } (\bar{a} \cdot n_k + \bar{b}) 1$]
return (**a**, **b**)}

Unrolled

```
do {a ~ normal  $\mu_a$   $\sigma_a$ ;  
    b ~ normal  $\mu_b$   $\sigma_b$ ;  
    y1 ~ normal (a •  $n_1$  + b) 1;  
    y2 ~ normal (a •  $n_2$  + b) 1;  
    :  
    yk ~ normal (a •  $n_k$  + b) 1;  
return ((y1, y2, ..., yk), (a, b))}
```

$$\lambda t \rightarrow$$

```
do { $\triangleleft$  ( $\bar{y}_1$ ,  $\bar{y}_2$ , ...,  $\bar{y}_k$ ) t  
       $\begin{bmatrix} \bar{a} \sim \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \sim \text{normal } (\bar{a} \cdot n_1 + \bar{b}) 1; \\ \bar{y}_2 \sim \text{normal } (\bar{a} \cdot n_2 + \bar{b}) 1; \\ \vdots \\ \bar{y}_k \sim \text{normal } (\bar{a} \cdot n_k + \bar{b}) 1 \end{bmatrix};$   
      return (a, b)}
```

```
do {a ~ normal  $\mu_a$   $\sigma_a$ ;  
    b ~ normal  $\mu_b$   $\sigma_b$ ;  
    y ~ plate  $k$  ( $\lambda i \rightarrow$  normal (a •  $n_i$  + b) 1);  
return (y, (a, b))}
```

$$\lambda t \rightarrow$$

```
do { $\triangleleft$   $\bar{y}$  t  
       $\begin{bmatrix} \bar{a} \sim \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim \text{normal } \mu_b \sigma_b; \\ \bar{y} \sim \text{plate } k \left( \lambda i \rightarrow \text{normal } (a \cdot n_i + b) 1 \right) \end{bmatrix}$   
      return (a, b)}
```

$y_k \sim \text{normal}(\bar{a} \cdot n_k + \bar{b}) 1;$

Unrolled

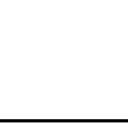


```

 $\lambda t \rightarrow$ 
do { $\triangleleft (\bar{y}_1, \bar{y}_2, \dots, \bar{y}_k) t$  
   $\begin{bmatrix} \bar{a} \sim \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \sim \text{normal}(\bar{a} \cdot n_1 + \bar{b}) 1; \\ \bar{y}_2 \sim \text{normal}(\bar{a} \cdot n_2 + \bar{b}) 1; \\ \vdots \\ \bar{y}_k \sim \text{normal}(\bar{a} \cdot n_k + \bar{b}) 1 \end{bmatrix};$ 
  return  $(a, b)$ 
}

```

Lifted



```

 $\lambda t \rightarrow$ 
do { $\triangleleft \bar{y} t$  
   $\begin{bmatrix} \bar{a} \sim \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim \text{normal } \mu_b \sigma_b; \\ \bar{y} \sim \text{plate } k (\lambda i \rightarrow \text{normal}(\bar{a} \cdot n_i + \bar{b}) 1) \end{bmatrix}$ 
  return  $(a, b)$ 
}

```

become

```

 $\lambda t \rightarrow$ 
do { $\triangleleft \bar{y}_1 t_1$  
   $\begin{bmatrix} \bar{a} \sim \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim \text{normal } \mu_b \sigma_b; \\ \bar{y}_1 \sim \text{normal}(\bar{a} \cdot n_1 + \bar{b}) 1; \\ \bar{y}_2 \sim \text{normal}(\bar{a} \cdot n_2 + \bar{b}) 1; \\ \vdots \\ \bar{y}_k \sim \text{normal}(\bar{a} \cdot n_k + \bar{b}) 1; \\ \text{factor } (k = \text{size } t) \end{bmatrix};$ 
   $\triangleleft \bar{y}_2 t_2 \dots;$ 
   $\vdots$ 
   $\triangleleft \bar{y}_k t_k \dots;$ 
  return  $(a, b)$ 
}

```

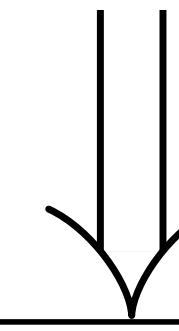
become

```

 $\lambda t \rightarrow$ 
do { $\triangleleft [\hat{j} \cdot k] \bar{y}[j] t_{\hat{j}}$  
   $\begin{bmatrix} \bar{a} \sim [] . \text{normal } \mu_a \sigma_a; \\ \bar{b} \sim [] . \text{normal } \mu_b \sigma_b; \\ \bar{y} \sim [\hat{i} \cdot k] . \text{normal}(\bar{a}[] \cdot n_{\hat{i}} + \bar{b}[]) 1; \\ \text{factor } [] . (k = \text{size } t) \end{bmatrix}$ 
  return  $(a, b)$ 
}

```

Lifted



Lifted
constraint

```
 $\lambda t \rightarrow$ 
do { $\triangleleft [\hat{j} \cdot k]$   $\bar{y}[j] t_{\hat{j}}$   $\begin{bmatrix} \bar{a} \leftarrow [] . \text{normal } \mu_a \sigma_a; \\ \bar{b} \leftarrow [] . \text{normal } \mu_b \sigma_b; \\ \bar{y} \leftarrow [\hat{i} \cdot k] . \text{normal } (\bar{a}[] \cdot n_{\hat{i}} + \bar{b}[]) 1; \\ \text{factor } [] . (k = \text{size } t) \end{bmatrix};$ 
.....}
.....
```

return $(a, b)\}$

Lifted binding

$[y_k \sim \text{normal}(\bar{a} \cdot n_k + \bar{b}) 1]$

Unrolled

```

 $\lambda t \rightarrow$ 
do { $\triangleleft \bar{y}_1 t_1$   $\left[ \bar{a} \sim \text{normal} \mu_a \sigma_a;$ 
 $\bar{b} \sim \text{normal} \mu_b \sigma_b;$ 
 $\bar{y}_1 \sim \text{normal} (\bar{a} \cdot n_1 + \bar{b}) 1;$ 
 $\bar{y}_2 \sim \text{normal} (\bar{a} \cdot n_2 + \bar{b}) 1;$ 
 $\vdots$ 
 $\bar{y}_k \sim \text{normal} (\bar{a} \cdot n_k + \bar{b}) 1;$ 
factor ( $k = \text{size } t$ )
 $\triangleleft \bar{y}_2 t_2 ...;$ 
 $\vdots$ 
 $\triangleleft \bar{y}_k t_k ...;$ 
return ( $a, b$ )}

```

```

 $\lambda t \rightarrow$ 
do { $\triangleleft \bar{y}_2 t_2$   $\left[ \bar{a} \sim \text{normal} \mu_a \sigma_a;$ 
 $\bar{b} \sim \text{normal} \mu_b \sigma_b;$ 
factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );
 $\bar{y}_2 \sim \text{normal} (\bar{a} \cdot n_2 + \bar{b}) 1;$ 
 $\vdots$ 
 $\bar{y}_k \sim \text{normal} (\bar{a} \cdot n_k + \bar{b}) 1;$ 
factor ( $k = \text{size } t$ )
 $\vdots$ 
 $\triangleleft \bar{y}_k t_k ...;$ 
return ( $a, b$ )}

```

Lifted

```

 $\lambda t \rightarrow$ 
do { $\triangleleft [\hat{j} \cdot k] \bar{y}[j] t_{\hat{j}}$   $\left[ \bar{a} \sim [] . \text{normal} \mu_a \sigma_a;$ 
 $\bar{b} \sim [] . \text{normal} \mu_b \sigma_b;$ 
 $\bar{y} \sim [\hat{i} \cdot k] . \text{normal} (\bar{a}[] \cdot n_{\hat{i}} + \bar{b}[]) 1;$ 
factor [] . ( $k = \text{size } t$ )
return ( $a, b$ )}

```

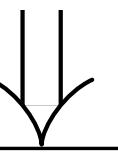
Unrolled

```
λ t →  
do { ◁  $\bar{y}_2$   $t_2$  [  $\bar{a} \leftarrow \text{normal } \mu_a \sigma_a;$   
   $\bar{b} \leftarrow \text{normal } \mu_b \sigma_b;$   
  factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );  
   $\bar{y}_2 \leftarrow \text{normal } (\bar{a} \cdot n_2 + \bar{b}) 1;$   
  :  
   $\bar{y}_k \leftarrow \text{normal } (\bar{a} \cdot n_k + \bar{b}) 1;$   
  factor (k = size t)  
  :  
  ◁  $\bar{y}_k$   $t_k$  ...;  
  return (a, b)}
```

Lifted

```
λ t →  
do { ◁  $\bar{y}_k$   $t_k$  [  $\bar{a} \leftarrow \text{normal } \mu_a \sigma_a;$   
   $\bar{b} \leftarrow \text{normal } \mu_b \sigma_b;$   
  factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );  
  factor (dNorm ( $a \cdot n_2 + b$ ) 1  $t_2$ );  
  :  
   $\bar{y}_k \leftarrow \text{normal } (\bar{a} \cdot n_k + \bar{b}) 1;$   
  factor (k = size t)  
  return (a, b)}
```

Unrolled



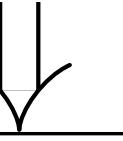
Lifted



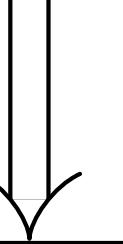
```
λ t →  
do {⟨ a ← normal μ_a σ_a;  
b ← normal μ_b σ_b;  
factor (dNorm (a · n_1 + b) 1 t_1);  
factor (dNorm (a · n_2 + b) 1 t_2);  
⋮  
factor (dNorm (a · n_k + b) 1 t_2);  
factor (k = size t)  
return (a, b)}
```

become

Unrolled



```
 $\lambda t \rightarrow$ 
do { $\bar{a} \leftarrow \text{normal } \mu_a \sigma_a;$ 
     $\bar{b} \leftarrow \text{normal } \mu_b \sigma_b;$ 
    factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );
    factor (dNorm ( $a \cdot n_2 + b$ ) 1  $t_2$ );
    :
    factor (dNorm ( $a \cdot n_k + b$ ) 1  $t_2$ );
    factor ( $k = \text{size } t$ )
  return ( $a, b$ )}
```



```
 $\lambda t \rightarrow$ 
do { $a \leftarrow \text{normal } \mu_a \sigma_a;$ 
     $b \leftarrow \text{normal } \mu_b \sigma_b;$ 
    factor (dNorm ( $a \cdot n_1 + b$ ) 1  $t_1$ );
    factor (dNorm ( $a \cdot n_2 + b$ ) 1  $t_2$ );
    :
    factor (dNorm ( $a \cdot n_k + b$ ) 1  $t_k$ );
    factor ( $k = \text{size } t$ );
  return ( $a, b$ )}
```

Lifted



```
 $\lambda t \rightarrow$ 
do { $\bar{a} \leftarrow [] . \text{normal } \mu_a \sigma_a;$ 
     $\bar{b} \leftarrow [] . \text{normal } \mu_b \sigma_b;$ 
    factor [ $j \cdot k$ ] . (dNorm ( $\bar{a}[] \cdot n_{\hat{j}} + \bar{b}[]$ ) 1  $t_{\hat{j}}$ );
    factor [] . ( $k = \text{size } t$ );
  return ( $a, b$ )}
```



```
 $\lambda t \rightarrow$ 
do { $a \leftarrow \text{normal } \mu_a \sigma_a;$ 
     $b \leftarrow \text{normal } \mu_b \sigma_b;$ 
     $_ \leftarrow \text{plate } k (\lambda i \rightarrow \text{factor (dNorm } ( $a \cdot n_i + b$ ) 1  $t_i)$ )
    factor ( $k = \text{size } t$ );
  return ( $a, b$ )}$ 
```

$$naiveBayes : \mathbb{N} \rightarrow \mathbb{N} \rightarrow \mathbb{N} \rightarrow \mathbb{N} \rightarrow \mathbb{M}(\langle\langle \mathbb{N} \rangle\rangle \times \langle \mathbb{N} \rangle) \quad (6.38)$$

$$naiveBayes = \lambda sizeVocab. \lambda numLabels. \lambda numDocs. \lambda sizeEachDoc. \quad (6.39)$$

```
do { $\beta \sim$  plate  $numLabels \_.$  dirichlet (array  $sizeVocab \_.$  1);  
     $\theta \sim$  dirichlet (array  $numLabels \_.$  1);  
     $\zeta \sim$  plate  $numDocs \_.$  categorical  $\theta$ ;  
     $ds \sim$  plate  $numDocs \_.$  i.  
        plate  $sizeEachDoc \_.$  categorical  $\beta[\zeta[i]]$ ;  
    return ( $ds, \zeta$ )}
```

disintegrate[◊] (*naiveBayes sizeVocab numLabels numDocs sizeEachDoc*) *t* (6.41)

⇒ do { $\beta \sim \text{plate numLabels } _. \text{dirichlet} (\text{array sizeVocab } _. 1);$ (6.42)

$\theta \sim \text{dirichlet} (\text{array numLabels } _. 1);$

$\zeta \sim \text{plate numDocs } _. \text{categorical } \theta;$

$_ \sim \text{plate numDocs } i.$

plate *sizeEachDoc j.*

do {factor ($\beta[\zeta[i]][t[i][j]] \div \text{sum } \beta[\zeta[i]]$);

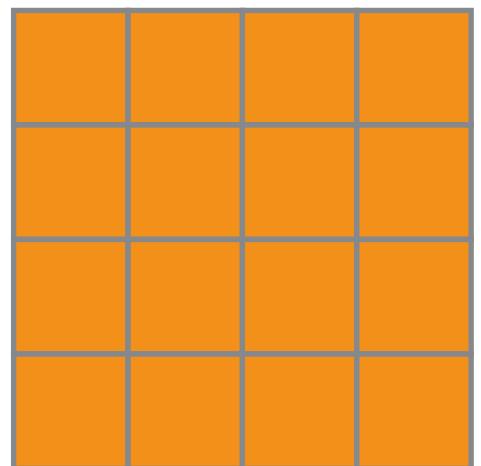
return ()};

return $\zeta\}$

What works

$\hat{i} \cdot k$

Index variable Size

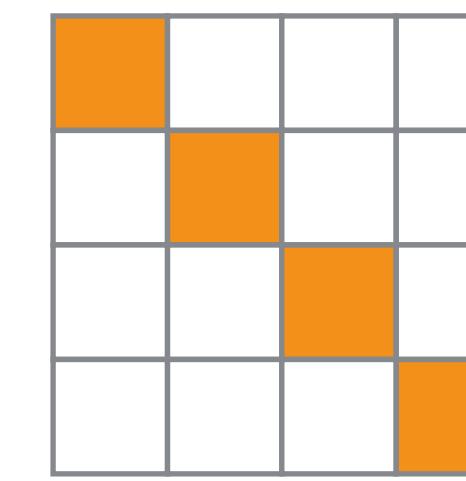


Observing whole arrays,
with copying, mapping,
and transposing

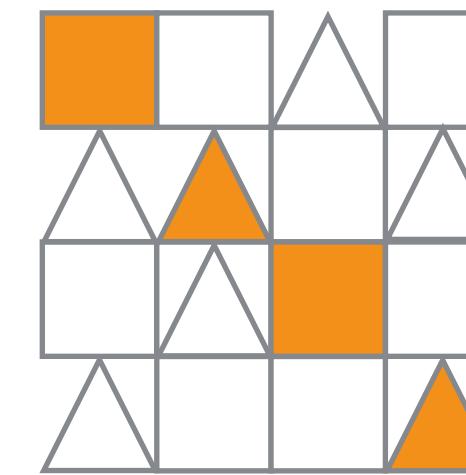
0	1	2	3	4	5	6	7	8	9
0	1	2	3	4	5	6	7	8	9
0	1	2	3	4	5	6	7	8	9
0	1	2	3	4	5	6	7	8	9
0	1	2	3	4	5	6	7	8	9
0	1	2	3	4	5	6	7	8	9

Models from R2
probabilistic
programming suite

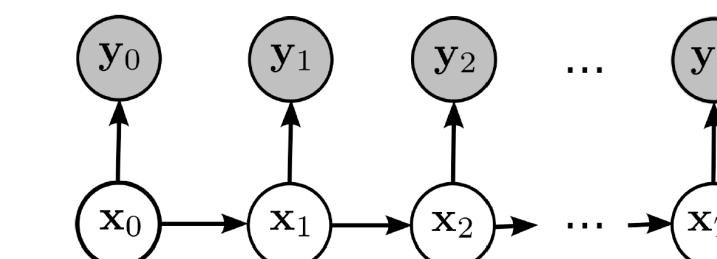
What we want to work



Observing parts of arrays

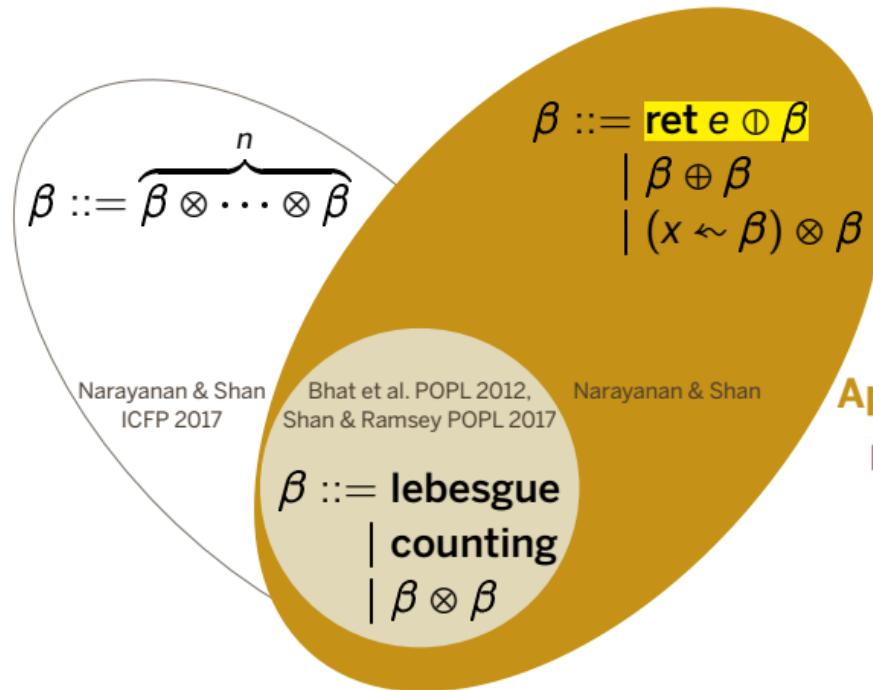


Conditionals inside arrays



Chain-like dependencies
between array elements

A growing variety of base measures



Discrete-continuous mixtures

Disjoint sums

Dependent products

Applications:

- ▶ clamped model/observation
(GPA, Tobit, camera)
 - ▶ likelihood ratio, importance sampling, mutual information
 - ▶ belief update, Gibbs sampling
- ▶ Metropolis-Hastings sampling
 - ▶ single site
 - ▶ reversible jump, light transport

Clamped observation requires mixed base

$x \leftarrow \text{normal}$

$y \leftarrow \text{normal}$

$$t = 5 \cdot x + 0.1 \cdot y$$

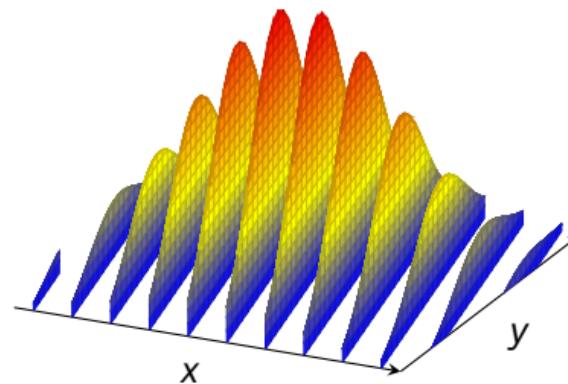
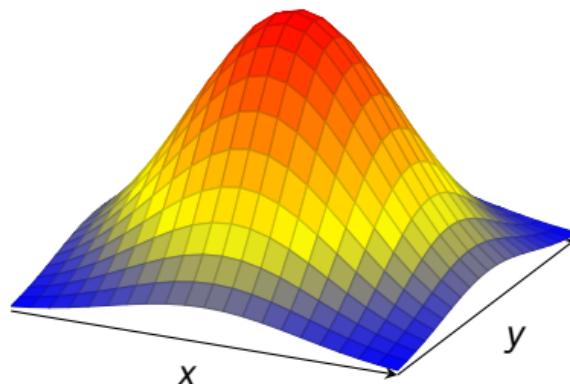
$$t' = \max\{-3, \min\{+3, t\}\}$$

$$p = (x, y)$$

\neq

$t' \leftarrow \text{lebesgue}$

$p \leftarrow ???$



Clamped observation requires mixed base

$x \leftarrow \text{normal}$

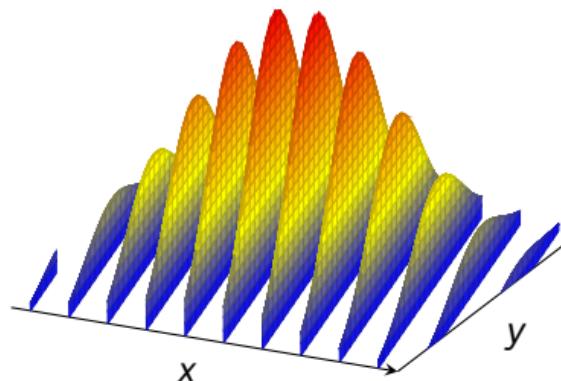
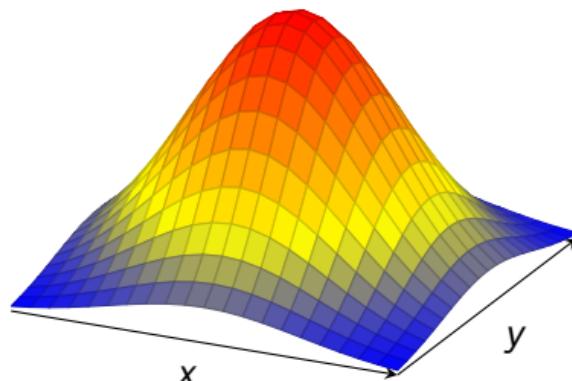
$y \leftarrow \text{normal}$

$t = 5 \cdot x + 0.1 \cdot y$

$t' \leftarrow (\text{factor } \langle t < -3 \rangle; \text{ret } -3) \oplus$
 $\quad (\text{factor } \langle t < +3 \rangle; \text{ret } +3) \oplus$
 $\quad (\text{factor } \langle |t| \leq 3 \rangle; \text{ret } t \quad)$

$p = (x, y)$

= $t' \leftarrow \text{ret } -3 \oplus \text{ret } +3 \oplus \text{lebesgue}$
 $p \leftarrow ???$



Base-checking disintegration

$x \sim \text{normal}$

=

$t' \sim \text{ret} -3 \odot \text{ret} +3 \odot \text{lebesgue}$

$y \sim \text{normal}$

$p \sim ???$

$t = 5 \cdot x + 0.1 \cdot y$

factor $\langle t < -3 \rangle$

$t' = -3$

$p = (x, y)$

$x \sim \text{normal}$

=

$t \sim \text{ret} -3 \odot \text{ret} +3 \odot \text{lebesgue}$

$y \sim \text{normal}$

$p \sim ???$

$t = 5 \cdot x + 0.1 \cdot y$

factor $\langle |t| \leq 3 \rangle$

$p = (x, y)$

Base-checking disintegration

```
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
t' = -3  
p = (x, y)
```

density

```
t' ~ ret -3 ⊖ ret +3 ⊖ lebesgue  
factor ⟨t' = -3⟩  
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
p = (x, y)
```

```
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨|t| ≤ 3⟩  
p = (x, y)
```

density

```
x ~ normal  
y ~ ret (10 · (-3 - 5 · x)) ⊖  
ret (10 · (+3 - 5 · x)) ⊖  
lebesgue  
t = 5 · x + 0.1 · y  
factor ⟨t ≠ {±3}⟩  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x, y)
```

reparameterize

```
t ~ ret -3 ⊖ ret +3 ⊖ lebesgue  
x ~ normal  
y = 10 · (t - 5 · x)  
factor 10  
factor ⟨t ∉ {±3}⟩  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x, y)
```

Base-inferring disintegration

$x \leftarrow \text{normal}$	=	$t' \leftarrow \mathbb{B}$
$y \leftarrow \text{normal}$		$p \leftarrow \text{???}$
$t = 5 \cdot x + 0.1 \cdot y$		
factor $\langle t < -3 \rangle$		
$t' = -3$		
$p = (x, y)$		

$x \leftarrow \text{normal}$	=	$t \leftarrow \mathbb{B}$
$y \leftarrow \text{normal}$		$p \leftarrow \text{???}$
$t = 5 \cdot x + 0.1 \cdot y$		
factor $\langle t \leq 3 \rangle$		
$p = (x, y)$		

Base-inferring disintegration

```
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
t' = -3  
p = (x,y)
```

density

```
t' ~ B  
divide (ret -3) B t'  
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
p = (x,y)
```

```
x ~ normal  
y ~ normal—density  
t = 5 · x + 0.1 · y  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

density

```
x ~ normal  
y ~ reparam (y ↦ 5 · x + 0.1 · y) B  
t = 5 · x + 0.1 · y  
reparameterize  
factor (10 / jacobian (y ↦ ...) B t)  
divide lebesgue B t  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

```
t ~ B  
x ~ normal  
y = 10 · (t - 5 · x)  
factor 10  
divide lebesgue B t  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

Base-inferring disintegration

```
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
t' = -3  
p = (x,y)
```

density

```
t' ~ B  
divide (ret -3) B t'  
x ~ normal  
y ~ normal  
t = 5 · x + 0.1 · y  
factor ⟨t < -3⟩  
p = (x,y)
```

```
x ~ normal  
y ~ normal—density  
t = 5 · x + 0.1 · y  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

density

```
x ~ normal  
y ~ reparam (y ↦ 5 · x + 0.1 · y) B  
t = 5 · x + 0.1 · y  
reparameterize  
factor (10 / jacobian (y ↦ ...) B t)  
divide lebesgue B t  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

```
t ~ B  
x ~ normal  
y = 10 · (t - 5 · x)  
factor 10  
divide lebesgue B t  
factor (dnorm y)  
factor ⟨|t| ≤ 3⟩  
p = (x,y)
```

Base-inferring disintegration

Infer principal base measure

divide $\begin{pmatrix} \text{ret} -3 & \oslash \\ \text{ret} +3 & \oslash \\ \text{lebesgue} \end{pmatrix}$ B

divide (ret -3) B t'

divide (ret +3) B t'

divide lebesgue B t

Generalized density calculation

density : $\mathbb{M}\alpha \rightarrow \mathbb{M}\alpha \rightarrow \alpha \rightarrow \{\mathbb{R}_+\}$
density $\mu \nu t =$ let $\mu' = \mu \otimes \mathbf{return} ()$
 $\nu' = \nu \otimes \mathbf{return} ()$
 $\lambda = \text{infer } \mu' t + \text{infer } \nu' t$
 in $|\text{check } \mu' \lambda t| \div |\text{check } \nu' \lambda t|$

Generalized MCMC sampling

$mhg : \mathbb{M} \alpha \rightarrow (\alpha \rightarrow \mathbb{M} \alpha) \rightarrow \alpha \rightarrow \mathbb{M} \alpha$
 $mhg \eta Q x = \mathbf{do} \{y \leftarrow Q x;$
 $r_{xy} \leftarrow \mathbf{return} (greenRatio \eta Q (x, y));$
 $a_{xy} \leftarrow \mathbf{return} \min(1, r_{xy});$
 $b \leftarrow \mathbf{bern} a_{xy};$
 $\mathbf{return} (\mathbf{if} b \mathbf{then} y \mathbf{else} x)\}$

$greenRatio : \mathbb{M} \alpha \rightarrow (\alpha \rightarrow \mathbb{M} \alpha) \rightarrow (\alpha \times \alpha) \rightarrow \{\mathbb{R}_+\}$
 $greenRatio \eta Q = density (fmap switch (\eta \otimes= Q)) (\eta \otimes= Q)$

$switch : (\alpha \times \beta) \rightarrow (\beta \times \alpha)$
 $switch p = (\text{snd } p, \text{fst } p)$

$(\otimes=) : \mathbb{M} \alpha \rightarrow (\alpha \rightarrow \mathbb{M} \beta) \rightarrow \mathbb{M} (\alpha \times \beta)$
 $m \otimes= k = \mathbf{do} \{x \leftarrow m; y \leftarrow k x; \mathbf{return} (x, y)\}$

Exact calculation

for approximate computation

<https://github.com/pravnar/disintegrating-mixtures>

Automatic differentiation

for gradient descent

Automatic disintegration

for inference and sampling

Generalizes density, conditioning

Derived by equational reasoning

A variety of base measures

Mixtures, disjoint sums,
dependent products

Infer principal base measure

