

From high-level inference algorithms to efficient code

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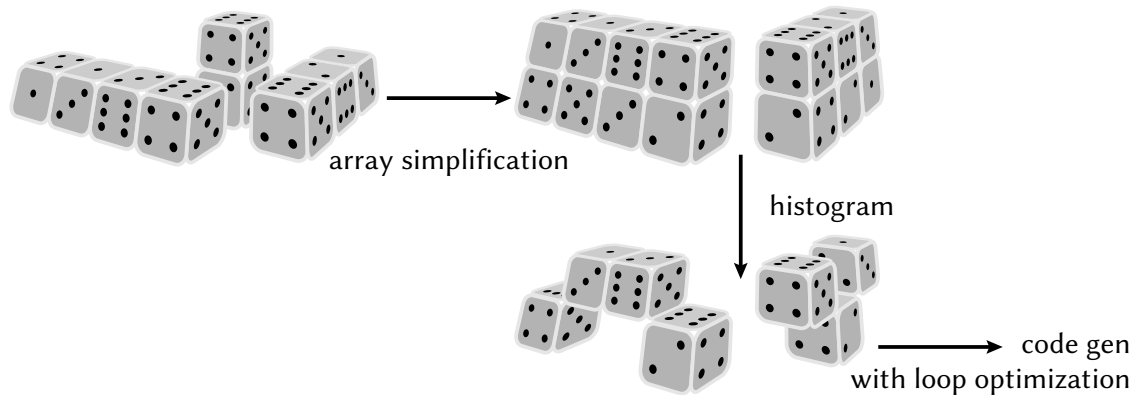
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“Algorithm”

- ▶ arithmetic
- ▶ sorting
- ▶ differentiation
- ▶ **sampling**



Array simplification

Goals

- ▶ Make fewer random choices
- ▶ Avoid weighting samples

Capabilities

- ▶ Eliminate latent variables
(aka Rao-Blackwellization, collapse, marginalization, integrating out)
- ▶ Recognize primitive densities
(in particular, conjugacy relationships between prior and likelihood)

Techniques

- ▶ Random arrays denote high- and arbitrary-dimensional integrals
- ▶ The unproduct operation:
if $\text{unproduct}(e, \vec{x}, i)$ returns the expression pair $(e', g(\vec{x}[i]))$ then $e = e' \cdot \prod_i g(\vec{x}[i])$

Before histogram

Gaussian model

$$\begin{aligned} & \sum_j (y[j] - x)^2 \\ &= \sum_j y[j]^2 \\ & - 2x \sum_j y[j] \\ & + x^2 \sum_j 1 \end{aligned}$$

Gaussian mixture model

$$\begin{aligned} \sum_j (y[j] - x[\ell[j]])^2 &= \sum_k \sum_j \begin{cases} (y[j] - x[k])^2 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} \\ &= \sum_k \sum_j \begin{cases} y[j]^2 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} \\ & - \sum_k 2x[k] \sum_j \begin{cases} y[j] & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} \\ & + \sum_k x[k]^2 \sum_j \begin{cases} 1 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

After histogram

$$\begin{aligned} \sum_{j=0}^{n-1} y[j]^2 &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Add}(y[j]^2)) \\ &\quad \text{in } hist \\ \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Idx}_k^m(\ell[j], \text{Add}(y[j]^2))) \\ &\quad \text{in } hist[k] \end{aligned}$$

After histogram

$$\sum_{j=0}^{n-1} y[j]^2 = \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Add}(y[j]^2)) \text{ in } hist$$

$$\sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} = \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Idx}_k^m(\ell[j], \text{Add}(y[j]^2))) \text{ in } hist[k]$$

$$\frac{\begin{array}{c} [j : \mathbb{N}] \\ \vdots \\ e : \mathbb{R} \end{array}}{\text{Add}(e) \triangleright_j \mathbb{R}} \quad \frac{\begin{array}{c} [j : \mathbb{N}] \quad [k : \mathbb{N}] \\ \vdots \quad \vdots \\ b : \mathbb{N} \quad e : \mathbb{N} \quad r \triangleright_j T \end{array}}{\text{Idx}_k^b(e, r) \triangleright_j \mathbb{A} T} \quad \frac{\begin{array}{c} [j : \mathbb{N}] \\ \vdots \\ e : \mathbb{B} \quad r_1 \triangleright_j T_1 \quad r_2 \triangleright_j T_2 \end{array}}{\text{Split}(e, r_1, r_2) \triangleright_j T_1 \times T_2}$$

$$\frac{r_1 \triangleright_j T_1 \quad r_2 \triangleright_j T_2}{\text{Fanout}(r_1, r_2) \triangleright_j T_1 \times T_2} \quad \frac{}{\text{Nop} \triangleright_j \mathbb{1}} \quad \frac{\begin{array}{c} a : \mathbb{N} \quad b : \mathbb{N} \quad r \triangleright_j T \end{array}}{\text{Hist}_{j=a}^b(r) : T}$$

After histogram

$$\begin{aligned}
 \sum_{j=0}^{n-1} y[j]^2 &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Add}(y[j]^2)) \\
 &\quad \text{in } hist \\
 \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \ell[j] \\ 0 & \text{otherwise} \end{cases} &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Idx}_k^m(\ell[j], \text{Add}(y[j]^2))) \\
 &\quad \text{in } hist[k] \\
 \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \ell[j] \wedge k' = \ell'[j] \\ 0 & \text{otherwise} \end{cases} &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Idx}_k^m(\ell[j], \text{Idx}_{k'}^{m'}(\ell'[j], \text{Add}(y[j]^2)))) \\
 &\quad \text{in } hist[k][k'] \\
 \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \begin{cases} \ell[j] & j \neq j^* \\ \ell^* & \text{otherwise} \end{cases} \\ 0 & \text{otherwise} \end{cases} &= \text{let } (hist_1, (hist_2, ())) \\
 &\quad = \text{Hist}_{j=0}^{n-1}(\text{Split}(j \neq j^*, \text{Idx}_k^m(\ell[j], \text{Add}(y[j]^2)), \\
 &\quad \quad \quad \text{Fanout}(\text{Add}(y[j]^2), \text{Nop}))) \\
 &\quad \text{in } hist_1[k] + \begin{cases} hist_2 & k = \ell^* \\ 0 & \text{otherwise} \end{cases}
 \end{aligned}$$

After histogram

$$\begin{array}{c}
 \frac{[j : \mathbb{N}] \quad \vdots \quad e : \mathbb{R}}{\text{Add}(e) \triangleright_j \mathbb{R}} \quad \frac{[j : \mathbb{N}] \quad [k : \mathbb{N}] \quad \vdots \quad b : \mathbb{N} \quad e : \mathbb{N} \quad r \triangleright_j T}{\text{Idx}_k^b(e, r) \triangleright_j \mathbb{A} T} \quad \frac{[j : \mathbb{N}] \quad \vdots \quad e : \mathbb{B} \quad r_1 \triangleright_j T_1 \quad r_2 \triangleright_j T_2}{\text{Split}(e, r_1, r_2) \triangleright_j T_1 \times T_2} \\
 \\
 \frac{r_1 \triangleright_j T_1 \quad r_2 \triangleright_j T_2}{\text{Fanout}(r_1, r_2) \triangleright_j T_1 \times T_2} \quad \frac{}{\text{Nop} \triangleright_j \mathbb{1}} \quad \frac{a : \mathbb{N} \quad b : \mathbb{N} \quad r \triangleright_j T}{\text{Hist}_{j=a}^b(r) : T}
 \end{array}$$

$$\begin{aligned}
 \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \ell[j] \wedge k' = \ell'[j] \\ 0 & \text{otherwise} \end{cases} &= \text{let } hist = \text{Hist}_{j=0}^{n-1}(\text{Idx}_k^m(\ell[j], \text{Idx}_{k'}^{m'}(\ell'[j], \text{Add}(y[j]^2)))) \\
 &\quad \text{in } hist[k][k'] \\
 \\
 \sum_{j=0}^{n-1} \begin{cases} y[j]^2 & k = \begin{cases} \ell[j] & j \neq j^* \\ \ell^* & \text{otherwise} \end{cases} \\ 0 & \text{otherwise} \end{cases} &= \text{let } (hist_1, (hist_2, ())) \\
 &\quad = \text{Hist}_{j=0}^{n-1}(\text{Split}(j \neq j^*, \text{Idx}_k^m(\ell[j], \text{Add}(y[j]^2)), \\
 &\quad \quad \quad \text{Fanout}(\text{Add}(y[j]^2), \text{Nop}))) \\
 &\quad \text{in } hist_1[k] + \begin{cases} hist_2 & k = \ell^* \\ 0 & \text{otherwise} \end{cases}
 \end{aligned}$$

Ablation study

Table: Run time in seconds (mean over 1000 trials and standard error) of one sweep of Gibbs sampling with $m = 50$ and $n = 10000$. Slowdown is compared to full optimization.

Optimizations	Time in seconds	Slowdown
No optimizations	471.441 ± 0.5973	1848 ×
No histogram	460.596 ± 0.1514	1805 ×
No LICM and loop fusion	328.736 ± 0.1019	1289 ×
No loop fusion	0.471 ± 0.0032	1.8×
No run-time specialization	2.422 ± 0.0054	9.5×
Full optimization	0.255 ± 0.0005	—

Histogram implementation

$$\text{histogram}(C[\begin{smallmatrix} e_1 \\ e_2 \end{smallmatrix} \begin{smallmatrix} e \\ \text{otherwise} \end{smallmatrix}], j) \longrightarrow \left(\text{Fanout}(m_1, m_2), \lambda(hist_1, hist_2). \begin{smallmatrix} f_1(hist_1) \\ f_2(hist_2) \end{smallmatrix} \begin{smallmatrix} e \\ \text{otherwise} \end{smallmatrix} \right)$$

where $(m_k, f_k) = \text{histogram}(C[e_k], j)$ and e does not depend on j

$$\text{histogram}(C[\begin{smallmatrix} e_1 \\ e_2 \end{smallmatrix} \begin{smallmatrix} e \\ \text{otherwise} \end{smallmatrix}], j) \longrightarrow (\text{Split}(e, m_1, m_2), \lambda(hist_1, hist_2). f_1(hist_1) + f_2(hist_2))$$

where $(m_k, f_k) = \text{histogram}(C[e_k], j)$

$$\text{histogram}(\begin{smallmatrix} a \\ 0 \end{smallmatrix} \begin{smallmatrix} i=e \\ \text{otherwise} \end{smallmatrix}, j) \longrightarrow (\text{Idx}_i^m(e, r), \lambda hist. \begin{smallmatrix} f(hist[i]) \\ 0 \end{smallmatrix} \begin{smallmatrix} i \in \{0, \dots, m-1\} \\ \text{otherwise} \end{smallmatrix}))$$

where $(r, f) = \text{histogram}(a, j)$, i is a loop-bound variable that does not depend on j ,
and the context entails that $i \in \{0, \dots, m-1\}$ or $e \in \{0, \dots, m-1\}$

$$\text{histogram}(0, j) \longrightarrow (\text{Nop}, \lambda hist. 0)$$

$$\text{histogram}(e, j) \longrightarrow (\text{Add}(e), \lambda hist. hist)$$

Figure: The histogram operation: if $\text{histogram}(e, j)$ returns the expression pair (r, f) then $\sum_{j=0}^{n-1} e = f(\text{Hist}_{j=0}^{n-1}(r))$. C denotes a context. These rewriting rules are applied top-down, except the second and third rules are prioritized by choosing the rule for which the innermost scope of the free variables $FV(e) \setminus \{j\}$ is outermost.

Code gen with loop optimization

