

Lecture 7. Weighted Sampling

Note Title

4/16/2006

Weighted Sample

A set of weighted samples $\{(x^{(j)}, w^{(j)}) : j=1 \dots m\}$ is called proper wrt π if for any square integrable function $h(\cdot)$.

$$E[h(x^{(j)}) w^{(j)}] = C E_{\pi} h(x), \quad j=1 \dots m.$$

C is a normalization constant

Joint distribution $g(w, x)$ for weights & samples.

Requires: $E_g \left(\frac{h(x) w}{E_g(w)} \right) = E_{\pi} (h(x))$

(see next page for details)

which implies

$$E_g(w|x) g(x) = \pi(x) (*)$$

(*) necessary and sufficient condition.

Importance Sampling is a special case where w is a deterministic function of x i.e. $w = \pi(x)/g(x)$.

Note: express $g(w, x) = g(w|x) g(x)$

Now, we show connection to rejection sampling.

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Proof of statements from first page.

Require:

$$\sum_{x,w} w h(x) g(x,w) = c \sum_x \pi(x) h(x)$$

where $g(x,w) = g(w|x)g(x)$.

If we want this to be true for any $h(x)$, then we need

$$\sum_w w g(x,w) = c \pi(x)$$

with normalization

$$\sum_{x,w} w h(x) g(x,w) = \sum_x \pi(x) h(x)$$
$$\frac{\sum_{x,w} w h(x) g(x,w)}{\sum_{x,w} w g(x,w)} = \frac{\sum_x \pi(x) h(x)}{\sum_x \pi(x)}$$

Alternatively, need $\frac{\sum_w w g(x,w)}{\sum_{w,x} w g(x,w)} = \pi(x)$

Clearly, importance sampling is a special case

$$\text{set } g(w|x) = \delta\left(w - \frac{\pi(x)}{g(x)}\right)$$

* Dirac delta function

i.e. the weight w is a function $\frac{\pi(x)}{g(x)}$ of the sample x (no randomness).

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Rejection Sampling as Weighted Sampling

Recall Rejection Sampling.

$l(x) = c \pi(x)$ is known (c unknown)

Pick $g(x)$ & M

s.t. $Mg(x) \geq l(x)$

Sample in two stages:

(i) sample x from $g(x)$

(ii) accept sample with prob $r(x) = l(x)/Mg(x)$

In context of weighted sampling.

$$g(x, w) = g(w|x) g(x)$$

Assign sample x a weight w $w = 1$ or $w = 0$

$$\text{Define: } g(w=1|x) = \frac{l(x)}{Mg(x)} \quad \left\{ \begin{array}{l} g(w=0|x) \\ = 1 - g(w=1|x) \end{array} \right.$$

$$\begin{aligned} \sum_{x,w} w h(x) g(x,w) &= \sum_x h(x) g(w=1|x) g(x) \\ &= \sum_x h(x) \frac{l(x)}{Mg(x)} g(x) = \frac{c}{M} \sum_x h(x) \pi(x) \end{aligned} \quad \text{as required}$$

$$\text{Also } \sum_{x,w} w g(x,w) = \sum_x g(w=1|x) g(x) = \frac{c}{M} \sum_x \pi(x) = \frac{c}{M}$$

Hence: $\frac{\frac{1}{M} \sum_{i=1}^m w_i h(x_i)}{\frac{1}{M} \sum_{i=1}^m w_i}$ is an estimator of $\sum_x h(x) \pi(x)$. Justifies rejection sampling.

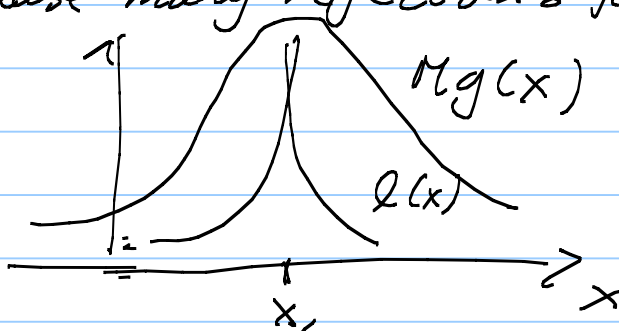
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Rejection Control.

want to get the best aspects of rejection and importance sampling.

Problem with Rejection Sampling — enforcing condition $\frac{L(x)}{Mg(x)} \leq 1$ is problematic. Strict enforcement may cause many rejections for some values of x . e.g.

Satisfying condition at x_c — means high rejection rate elsewhere.



Problem with Importance Sampling

Samples with small weights contribute little to the estimate, but require evaluating $h(x)$ — which can be computationally expensive.

Combine Rejection & Importance Sampling

- Relax the requirement $\frac{L(x)}{Mg(x)} \leq 1$.
- Reject samples with small weights.
(don't waste time evaluating $h(x)$)

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Rejection Control.

Sample x from $g(x)$.

Define
$$r(x) = \min \left\{ 1, \frac{\pi(x)}{c g(x)} \right\}$$

" c " can be anything (i.e. not just the normalizing constant of $\pi(x)$).

Define:

$\delta(\cdot)$
delta-function.

$$g(\omega | x) = \delta(\omega - \frac{\pi(x) \cdot q_c}{c g(x) r(x)}) r(x) + \delta(\omega) \{1 - r(x)\}.$$

i.e. ω can take value 0 (reject)

or $\frac{\pi(x) \cdot q_c}{c g(x) r(x)}$ (importance weight)
 q_c - const.

$$\begin{aligned} \sum_{x, \omega} h(x) \omega g(\omega | x) g(x) &= \sum_x h(x) \frac{\pi(x) \cdot q_c}{c g(x) r(x)} r(x) g(x) \\ &= \frac{q_c}{c} \sum_x h(x) \pi(x). \end{aligned}$$

Also
$$\sum_{x, \omega} \omega g(\omega | x) g(x) = \sum_x \frac{\pi(x) \cdot q_c}{c g(x) r(x)} r(x) g(x) = q_c / c.$$

weight
$$\frac{\pi(x) \cdot q_c}{c g(x) r(x)}.$$

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Rejection Control.

Hence:

$$\frac{\sum_{x, \omega} h(x) \omega g(\omega | x) g(x)}{\sum_{x, \omega} \omega g(\omega | x) g(x)} = \sum_x \pi(x) h(x)$$

So sample (ω, x) from

$$g(\omega, x) = g(\omega | x) g(x)$$

defined on previous page.

Then $\frac{\frac{1}{m} \sum_{i=1}^m h(x^i) \omega_i}{\frac{1}{m} \sum_{i=1}^m \omega_i}$ will converge to $\sum_x \pi(x) h(x)$ as $m \rightarrow \infty$.

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Rejection Control.

(Note: error in lecture)

Define $g^*(x) = \frac{r(x)g(x)}{q_c}$ with $q_c = \sum_x r(x)g(x)$.

Then $g(w|x)g(x) = \frac{q_c \delta(w - \frac{\pi(x)}{c g^*(x)})}{c g^*(x)} g^*(x) + \delta(w) \{1 - r(x)\} g(x)$

So Rejection Control (RC) is like importance sampling from $g^*(x)$, but with the possibility of assigning zero weight (second term)

Note: Sampling from $\frac{r(x)g(x)}{q_c}$ is like sampling from $g(x)$ and then accepting the sample with probability $r(x)$. (as in CKS)
the weight given $\frac{\pi(x)}{c g^*(x)} = \frac{\pi(x) \cdot q_c}{c g(x) r(x)}$.
same weight as (CKS).

Theorem (page 45 Liu)

$$\text{var}_{g^*} \left\{ \frac{\pi(x)}{g^*(x)} \right\} \leq \text{var}_g \left\{ \frac{\pi(x)}{g(x)} \right\}$$

So rejection control is better than sampling from $g(\cdot)$.