Non-negative Monte Carlo estimation of f-divergences

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Abstract

We show how to guarantee non-negative Monte Carlo estimations of f-divergences by considering the corresponding extended f-divergences.

1 Problem with naive Monte Carlo estimations of f-divergences

Let (X, F, μ) be a probability space [4] with X denoting the sample space, F the σ-algebra, and μ a reference positive measure. The f-divergence [2, 5] between two probability measures P and Q both absolutely continuous with respect to μ for a convex generator $f : (0, \infty) \to \mathbb{R}$ strictly convex at 1 and satisfying $f(1) = 0$ is

$$I_f(P : Q) = I_f(p : q) = \int p(x) f\left(\frac{q(x)}{p(x)}\right) \mathrm{d}\mu(x),$$

where $P = p\mathrm{d}\mu$ and $Q = q\mathrm{d}\mu$ (i.e., p and q are Radon-Nikodym derivatives with respect to μ). We use the following conventions:

$$0f\left(\frac{0}{0}\right) = 0, \quad f(0) = \lim_{u \to 0^+} f(u), \quad \forall a > 0, 0f\left(\frac{a}{0}\right) = \lim_{u \to 0^+} uf\left(\frac{a}{u}\right) = a \lim_{u \to \infty} \frac{f(u)}{u}.$$

When $f(u) = -\log u$, we retrieve the Kullback-Leibler divergence (KLD):

$$D_{\mathrm{KL}}(p : q) = \int p(x) \log \frac{p(x)}{q(x)} \mathrm{d}\mu(x).$$

The KLD is usually difficult to calculate in closed-form, say, for example, between statistical mixture models [6]. A common technique is to estimate the KLD using Monte Carlo sampling using a proposal distribution r:

$$\widehat{\mathrm{KL}}_n(p : q) = \frac{1}{n} \sum_{i=1}^{n} \frac{p(x_i)}{r(x_i)} \log \frac{p(x_i)}{q(x_i)},$$

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where $x_1, \ldots, x_n \sim_{\text{iid}} r$. When r is chosen as p, the KLD can be estimated as

$$\widehat{\mathrm{KL}}_n(p:q) = \frac{1}{n}\sum_{i=1}^{n} \log \frac{p(x_i)}{q(x_i)}. \tag{1}$$

Monte Carlo estimators are consistent under mild conditions: $\lim_{n\rightarrow\infty} \widehat{\mathrm{KL}}_n(p:q) = \mathrm{KL}(p:q)$.

In practice, one problem when implementing Eq. 1, is that we may end up potentially with $\widehat{\mathrm{KL}}_n(p:q) < 0$. This may have disastrous consequences as algorithms implemented by programs consider non-negative divergences to execute a correct workflow. The potential negative value problem of Eq. 1 comes from the fact that $\sum_i p(x_i) \neq 1$ and $\sum_i q(x_i) \neq 1$.

2 Non-negative Monte Carlo estimation via extended f-divergences

One way to circumvent this problem is to consider the extended f-divergences:

Definition 1 (Extended f-divergence) *The extended f-divergence for a convex generator f, strictly convex at 1 and satisfying $f(1) = 0$ is defined by*

$$I_f^e(p:q) = \int p(x)\left(f\left(\frac{q(x)}{p(x)}\right) - f'(1)\left(\frac{q(x)}{p(x)} - 1\right)\right) \mathrm{d}\mu(x).$$

Indeed, for a strictly convex generator f, let us consider the scalar Bregman divergence [1]:

$$B_f(a:b) = f(a) - f(b) - (a-b)f'(b) \geq 0. \tag{2}$$

Setting $a = \frac{q(x)}{p(x)}$ and $b = 1$ in Eq. 2, and using the fact that $f(1) = 0$, we get

$$f\left(\frac{q(x)}{p(x)}\right) - \left(\frac{q(x)}{p(x)} - 1\right) f'(1) \geq 0.$$

Therefore we define the *extended f-divergences* as $I_f^e(p:q) = \int p(x) B_f\left(\frac{q(x)}{p(x)} : 1\right) \mathrm{d}\mu(x) \geq 0$:

$$I_f^e(p:q) = \int p(x)\left(f\left(\frac{q(x)}{p(x)}\right) - f'(1)\left(\frac{q(x)}{p(x)} - 1\right)\right) \mathrm{d}\mu(x) \geq 0. \tag{3}$$

Then we estimate the extended f-divergence using importance sampling of the integral with respect to distribution r, using n variates $x_1, \ldots, x_n \sim_{\text{iid}} p$ as:

$$\boxed{\hat{I}_{f,n}(p:q) = \frac{1}{n}\sum_{i=1}^{n} f\left(\frac{q(x_i)}{p(x_i)}\right) - f'(1)\left(\frac{q(x_i)}{p(x_i)} - 1\right) \geq 0.}$$

For example, for the KLD, we obtain the following Monte Carlo estimator:

$$\widehat{\mathrm{KL}}_n(p:q) = \frac{1}{n}\sum_{i=1}^{n}\left(\log\frac{p(x_i)}{q(x_i)} + \frac{q(x_i)}{p(x_i)} - 1\right) \geq 0, \tag{4}$$

since the extended KLD is

$$D_{\mathrm{KL}^e}(p:q) = \int \left(p(x) \log \frac{p(x)}{q(x)} + q(x) - p(x) \right) \mathrm{d}\mu(x).$$

Eq. 4 can be interpreted as a sum of scalar Itakura-Saito divergences since the Itakura-Saito divergence is scale-invariant: $\widehat{\mathrm{KL}}_n(p:q) = \frac{1}{n}\sum_{i=1}^n D_{\mathrm{IS}}(p(x_i):q(x_i))$ with the scalar Itakura-Saito divergence

$$D_{\mathrm{IS}}(a:b) = D_{\mathrm{IS}}\left(\frac{a}{b}:1\right) = \frac{a}{b} - \log\frac{a}{b} - 1 \geq 0,$$

a Bregman divergence obtained for the generator $f(u) = -\log u$.

Notice that the extended f-divergence is a f-divergence for the generator

$$f_e(u) = f(u) - f'(1)(u-1).$$

We check that the generator f_e satisfies both $f(1) = 0$ and $f'(1) = 0$, and we have $I_f^e(p:q) = I_{f_e}(p:q)$. Thus $D_{\mathrm{KL}^e}(p:q) = I_{f_{\mathrm{KL}}^e}(p:q)$ with $f_{\mathrm{KL}}^e(u) = -\log u + u - 1$.

Let us remark that we only need to have the scalar function strictly convex at 1 to ensure that $B_f\left(\frac{a}{b}:1\right) \geq 0$. Indeed, we may use the definition of Bregman divergences extended to strictly convex functions but not necessarily smooth functions [3, 7]:

$$B_f(x:y) = \max_{g(y)\in\partial f(y)} \{f(x) - f(y) - (x-y)g(y)\},$$

where $\partial f(y)$ denotes the subderivative of f at y.

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