Evidence lower bounds with built-in baselines

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December 26, 2022

1 Problem setup

The goal is to maximize the log marginal likelihood,

$$\log p(x) = \log \sum_{z} p(x, z), \tag{1}$$

for a latent variable model. The derivative of the above is

$$\nabla \log \sum_{z} p(x, z) = \frac{p(x, z)}{p(x)} \nabla \log p(x, z) = p(z \mid x) \nabla \log p(x, z), \tag{2}$$

the expected gradient under the posterior. When exact marginalization is intractable, a common approach is to introduce a variational approximation to the posterior $q(z \mid x)$ and optimize the lower bound

$$\log p(x) = \log \sum_{z} q(z \mid x) \frac{p(x, z)}{q(z \mid x)} \ge \sum_{z} q(z \mid x) \log \frac{p(x, z)}{q(z \mid x)}, \tag{3}$$

which allows for tractable Monte Carlo approximation. ¹

Empirically, we find directly optimizing this lower bound (3) to be more difficult than optimizing the marginal likelihood (1), often requiring a baseline:

$$\nabla_{q} \sum_{z} q(z \mid x) \log \frac{p(x, z)}{q(z \mid x)}$$

$$= \nabla_{q} \sum_{z} q(z \mid x) \log p(x \mid z) - KL[q(z \mid x)||p(z)]$$

$$= \nabla_{q} \sum_{z} q(z \mid x) (\log p(x \mid z) - B) - KL[q(z \mid x)||p(z)],$$

$$(4)$$

where the baseline B is not a function of z.² Computing this baseline B can be expensive, potentially requiring multiple evaluations of $p(x \mid z)$. A common choice of baseline is the sample-average baseline, where $B = \sum_{z' \in Z} \log p(x \mid z')$ and Z is a set of iid samples.³ Additionally, even in scenarios where exact marginalization is tractable, prior work has included a baseline. This begs the questions: Is a baseline necessary, and why does optimizing the marginal likelihood not require a baseline?

We show that the gradient of the marginal likelihood (2) already contains a built-in baseline, and use that to derive a simple and computable lower bound of the marginal likelihood (1) whose gradient does not require the manual engineering of a baseline.

The gap between the two is given by $KL[q(z \mid x)||p(z \mid x)]$.

²The derivative is a linear operator, and $\nabla \sum_{z} q(z \mid x) B = B \nabla \sum_{z} q(z \mid x) = B \cdot 0$.

³A more efficient alternative is the leave-one-out baseline, which is efficient if the results of $p(x \mid z)$ are already available for a set of iid z.

2 The gradient of logsumexp approximates the expoentiated regret

The key component of the marginal likelihood is the logsum exp operation, a smooth version of max: $\log \sum_z \exp f(z)$.⁴ Similar to the gradient of the marginal likelihood, the gradient of logsum exp is given by

$$\nabla \log \sum_{z' \in Z} \exp f(z') = \frac{e^{f(z)}}{\sum_{z' \in Z} e^{f(z')}} \nabla f(z) = e^{f(z) - \log \sum_{z' \in Z} e^{f(z')}} \nabla f(z) \approx \underbrace{e^{f(z) - \max_{z' \in Z} f(z')}}_{R} \nabla f(z).$$

The last approximation holds because logsum prize is a smooth approximation of max. We can therefore think of $\log \sum_{z' \in Z} \exp f(z') \approx \max_{z' \in Z} f(z)$ as a built-in baseline. R is also the exponentiated regret, the difference between a given f(z) and the best f(z). Since the regret is non-positive, the exponentiated regret is always between 0 and 1.

3 Variance analysis

TBD

 $^{^4 {\}rm log} \sum {\rm exp}(f(z))$ is perhaps better known as the log-partition function.