Contents

1 Unbiased Implicit Variational Inference

Based on Titsias and Ruiz [1].

- Authors introduce unbiased implicit variational inference (UIVI) that defines a flexible variational family. Like semi-implicit variational inference (SIVI), UIVI uses an implicit variational distribution $q_\theta(z) = \int q_\theta(z|\varepsilon)q(\varepsilon)d\varepsilon$ where $q_\theta(z|\varepsilon)$ is a reparameterizable distribution whose parameters can be outputs of some neural network g, i.e., $q_\theta(z|\varepsilon) = h(u; g(\varepsilon;\theta))$ with $u \sim q(u)$. Under two assumptions on the conditional $q_\theta(z|\varepsilon)$, the ELBO can be approximated via Monte Carlo sampling. In particular, the entropy component of the ELBO can be rewritten as an expectation w.r.t. the reverse conditional $q_\theta(\varepsilon|z)$. Efficient approximation of this expectation w.r.t. the reverse conditional is done by reusing samples from approximating the main expectation to initialize a MCMC sampler.
- Questions: TODO
  1. Can the gradient be pushed into the expectation? (Section 2.2)

References

[1] Michalis K Titsias and Francisco Ruiz. Unbiased implicit variational inference. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pages 167–176. PMLR, 2019.