Likelihood-free Posterior Density Learning for Uncertainty Quantification in Inference Problems

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Abstract
Generative models and those with computationally intractable likelihoods are widely used to describe complex systems in the natural sciences, social sciences, and engineering. Fitting these models to data requires likelihood-free inference methods that explore the parameter space without explicit likelihood evaluations, relying instead on sequential simulation, which comes at the cost of computational efficiency and extensive tuning. We develop an alternative framework called kernel-adaptive synthetic posterior estimation (KASPE) that uses deep learning to directly reconstruct the mapping between the observed data and a finite-dimensional parametric representation of the posterior distribution, trained on a large number of simulated datasets. We provide theoretical justification for KASPE and a formal connection to the likelihood-based approach of expectation propagation. Simulation experiments demonstrate KASPE's flexibility and performance relative to existing likelihood-free methods including approximate Bayesian computation in challenging inferential settings involving posteriors with heavy tails, multiple local modes, and over the parameters of a nonlinear dynamical system.

Keywords: Deep learning; likelihood-free inference; generative models.

Reference:
R. Zhang, O.A. Chkrebtii, D. Xiu. Likelihood-free Posterior Density Learning for Uncertainty Quantification in Inference Problems. Preprint at ArXiv:2508.00167, 2025.