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*High-dimensional Copula Variational Approximation Through Transformation*

Variational methods are attractive for computing Bayesian inference for highly parametrized models and large datasets where exact inference is impractical. They approximate a target distribution - either the posterior or an augmented posterior - using a simpler distribution that is selected to balance accuracy with computational feasibility. Here we approximate an element-wise parametric transformation of the target distribution as multivariate Gaussian or skew-normal. Approximations of this kind are implicit copula models for the original parameters, with a Gaussian or skew-normal copula function and flexible parametric margins. A key observation is that their adoption can improve the accuracy of variational inference in high dimensions at limited or no additional computational cost. We consider the Yeo-Johnson and G&H transformations, along with sparse factor structures for the scale matrix of the Gaussian or skew-normal. We also show how to implement efficient reparametrization gradient methods with both Gaussian and skew-normal copula variational families and illustrate the effectiveness of the proposed methods in a range of examples. (Joint work with Michael Smith and Ruben Loaiza-Maya.)