Efficient Bayesian reduced rank regression using Langevin Monte Carlo approach

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The problem of Bayesian reduced rank regression is considered in this paper. We propose, for the first time, to use Langevin Monte Carlo method in this problem. A spectral scaled Student prior distrbution is used to exploit the underlying low-rank structure of the coefficient matrix. We show that our algorithms are significantly faster than the Gibbs sampler in high-dimensional setting. Simulation results show that our proposed algorithms for Bayesian reduced rank regression are comparable to the state-of-the-art method where the rank is chosen by cross validation.

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Computational challenges of Empirical likelihood

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The emmpirical likelihood (EL) method is a well-known and established nonparametric method inroduced in 1988 by Owen [1]. During a few last decades new nonparametric EL-based methods have appeared as the alternatives to many classical statistical methods. This work is devoted to computational issues dealing with the EL versions based on the smoothed and non-smoothed estimating equations.

The smoohted version of EL first was introduced in 1993 by Chen and Hall [2] in the one-sample quantile setting. They discovered that by appropriate smoothing the coverage accuracy can be improved by $n^{-1/2}$ to order n^{-1}. Moreover, it can be further improved by Bartlett correction from order n^{-1} to n^{-2}. Since their foundings many scientists have used the smoothing principle especially for the inference of quantile differences, ROC curves, probability-probability and quantile-quantile plots (many two-sample problems based on smoothed EL have been implemented in the R package "EL" [3]).

The EL version based on non-smooth estimating equations was introduced by Molanes Lopez, Keilegom and Veraverbeke in 2009 [4]. They provided some simulation study regarding copulas and described the computational aspects of their work.

Our goal is to discuss the computational aspects of both methods, implement them and show an extensive simulation study and some applications to real datasets.

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Bayesian calibration of Arterial Windkessel model

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This work is motivated by personalized digital twins based on observations and physical models for treatment and prevention of Hypertension. The models we consider are the two and three parameters Windkessel models [1] (WK2 and WK3). These models simulate the blood pressure waveform given the blood inflow and a set of physically interpretable calibration parameters. The third parameter in WK3 function as a tuning parameter to better match observations. We focus on the inverse problem, i.e. to estimate the physical parameters given observations. The models are simplification of the real process and to account for model discrepancy we set up the estimation problem in a Bayesian calibration framework [2, 3]. This naturally solves the inverse problem accounting for uncertainty in the model formulation, in the parameter estimates and predictions.

The WK2 model offers physical interpretable parameters and therefore we adopt it as a computer model choice in a Bayesian calibration formulation. In a synthetic simulation study, we simulate noisy data from the WK3 model. We estimate the model parameters using conventional methods, i.e. least squares optimization and through the Bayesian calibration framework. It is demonstrated that our formulation can reconstruct the blood pressure waveform of the complex model, but most importantly can learn the parameters according to known mathematical connections between the two models. We also apply this formulation to a real case study, where data was obtained from a pilot randomized controlled trial study. Our approach is successful for both the simulation study and the real cases.

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Variational Bayes for inference on model and parameter uncertainty in Bayesian neural networks

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Bayesian neural networks (BNNs) have recently regained a significant amount of attention in the deep learning community due to the development of scalable approximate Bayesian inference techniques [1]. There are several advantages of using a Bayesian approach: Parameter and prediction uncertainties become easily available, facilitating rigorous statistical analysis. Furthermore, prior knowledge can be incorporated. However so far there have been no scalable techniques capable of combining both model (structural) and parameter uncertainty. In the presented piece of research [2] we introduce the concept of model uncertainty in BNNs and hence make inference in the joint space of models and parameters. Moreover, we suggest an adaptation of a scalable variational inference approach with reparametrization of marginal inclusion probabilities to incorporate the model space constraints. Experimental results on a range of benchmark data sets show that we obtain comparable accuracy results with the competing models, but based on methods that are much more sparse than ordinary BNNs. This is particularly the case in model selection settings, but also within a Bayesian model averaging setting a considerable sparsification is achieved. As expected, model uncertainties give higher, but more reliable uncertainty measures.

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