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Retraction: On Hilbert's 8th problem

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University of Chicago

Abstract. Two errata in the paper are given.

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Bimodal extension based on the skew-*t*-normal distribution

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Abstract. In this paper, a skew and uni-/bi-modal extension of the Student-*t* distribution is considered. This model is more flexible and has wider ranges of skewness and kurtosis than the other skew distributions in literature. Fisher information matrix for the proposed model and some submodels are derived. With a simulation study and some real data sets, applicability of the proposed models are illustrated.

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Key words and phrases. Skewness, kurtosis, bimodal density, Fisher information matrix, maximum likelihood estimation.

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Extreme-cum-median ranked set sampling

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Abstract. A mixture of Extreme Ranked Set Sampling (ERSS) and Median Ranked Set Sampling (MRSS) is introduced to obtain a more representative sample using three out of five number summary statistics [i.e., Minimum, Median and Maximum]. The proposed sampling scheme provides unbiased estimator of mean for symmetric population and gives moderate efficiency for both symmetric and asymmetric populations under perfect as well as imperfect rankings. Expressions for bias and asymptotic variance are presented. A simulation study is also conducted to observe the performance of the proposed estimator. Application of proposed sampling scheme is illustrated through a real life example.

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Key words and phrases. Median ranked set sampling, extreme ranked set sampling, ranking error, imperfect ranking.

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Inventory model of type (s, S) under heavy tailed demand with infinite variance

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Abstract. In this study, a stochastic process $X(t)$, which describes an inventory model of type (s, S) is considered in the presence of heavy tailed demands with infinite variance. The aim of this study is observing the impact of regularly varying demand distributions with infinite variance on the stochastic process $X(t)$. The main motivation of this work is, the publication by Geluk [*Proceedings of the American Mathematical Society* **125** (1997) 3407–3413] where he provided a special asymptotic expansion for renewal function generated by regularly varying random variables. Two term asymptotic expansion for the ergodic distribution function of the process $X(t)$ is obtained based on the main results proposed by Geluk [*Proceedings of the American Mathematical Society* **125** (1997) 3407–3413]. Finally, weak convergence theorem for the ergodic distribution of this process is proved by using Karamata theory.

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Exploring the constant coefficient of a single-index variation

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Abstract. We consider a problem of checking whether the coefficient of the scale and location function is a constant. Both the scale and location functions are modeled as single-index models. Two test statistics based on Kolmogorov–Smirnov and Cramér–von Mises type functionals of the difference of the empirical residual processes are proposed. The asymptotic distribution of the estimator for single-index parameter is derived, and the empirical distribution function of residuals is shown to converge to a Gaussian process. Moreover, the proposed test statistics can be able to detect local alternatives that converge to zero at a parametric convergence rate. A bootstrap procedure is further proposed to calculate critical values. Simulation studies and a real data analysis are conducted to demonstrate the performance of the proposed methods.

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Transdimensional transformation based Markov chain Monte Carlo

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Abstract. Variable dimensional problems, where not only the parameters, but also the number of parameters are random variables, pose serious challenge to Bayesians. Although in principle the Reversible Jump Markov Chain Monte Carlo (RJMCMC) methodology is a response to such challenges, the dimension-hopping strategies need not be always convenient for practical implementation, particularly because efficient "move-types" having reasonable acceptance rates are often difficult to devise.

In this article, we propose and develop a novel and general dimension-hopping MCMC methodology that can update all the parameters as well as the number of parameters simultaneously using simple deterministic transformations of some low-dimensional (often one-dimensional) random variable. This methodology, which has been inspired by Transformation based MCMC (TMCMC) of (*Stat. Mehodol.* (2014) **16** 100–116), facilitates great speed in terms of computation time and provides reasonable acceptance rates and mixing properties. Quite importantly, our approach provides a natural way to automate the move-types in variable dimensional problems. We refer to this methodology as Transdimensional Transformation based Markov Chain Monte Carlo (TTMCMC). Comparisons with RJMCMC in gamma and normal mixture examples demonstrate far superior performance of TTMCMC in terms of mixing, acceptance rate, computational speed and automation. Furthermore, we demonstrate good performance of TTMCMC in multivariate normal mixtures, even for dimension as large as 20. To our knowledge, there exists no application of RJMCMC for such high-dimensional mixtures.

As by-products of our effort on the development of TTMCMC, we propose a novel methodology to summarize the posterior distributions of the mixture densities, providing a way to obtain the mode of the posterior distribution of the densities and the associated highest posterior density credible regions. Based on our method, we also propose a criterion to assess convergence of variable-dimensional algorithms. These methods of summarization and convergence assessment are applicable to general problems, not just to mixtures.

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Bootstrap for correcting the mean square error of prediction and smoothed estimates in structural models

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Abstract. It is well known that the uncertainty in the estimation of parameters produces the underestimation of the mean square error (MSE) both for in-sample and out-of-sample estimation. In the state space framework, this problem can affect confidence intervals for smoothed estimates and forecasts, which are generally built by state vector predictors that use estimated model parameters. In order to correct this problem, this paper proposes and compares parametric and nonparametric bootstrap methods based on procedures usually employed to calculate the MSE in the context of forecasting and smoothing in state space models. The comparisons are performed through an extensive Monte Carlo study which illustrates, empirically, the bias reduction in the estimation of MSE for prediction and smoothed estimates using the bootstrap approaches. The finite sample properties of the bootstrap procedures are analyzed for Gaussian and non-Gaussian assumptions of the error term. The procedures are also applied to real time series, leading to satisfactory results.

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Fitting mixed models to messy longitudinal data: A case study involving estimation of post mortem intervals

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Abstract. Non-linear mixed models are useful in many practical longitudinal data problems, especially when they are derived as solutions to differential equations generated by subject matter theoretical considerations. When this underlying rationale is not available, practitioners are faced with the dilemma of choosing a model from the numerous ones available in the literature. The situation is even worse for messy data where interpretation and computational problems are frequent. This is the case with a pilot observational study conducted at the School of Medicine of the University of São Paulo in which a new method to estimate the time since death (post-mortem interval—PMI) is proposed. In particular, the attenuation of the density of intra-cardiac hypostasis (concentration of red cells in the vascular system by gravity) obtained from a series of tomographic images was observed in the thoraces of 21 bodies of hospitalized patients with known time of death. The images were obtained at different instants and not always at the same conditions for each body, generating a set of messy data. In this context, we consider three *ad hoc* models to analyse the data, commenting on the advantages and caveats of each approach.

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Key words and phrases. Autopsy, calibration, computed tomography, diagnostics, hypostasis, linear mixed models, post-mortem interval, residual analysis.

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The equivalence of dynamic and static asset allocations under the uncertainty caused by Poisson processes

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Abstract. We investigate the equivalence of dynamic and static asset allocations in the case where the price process of a risky asset is driven by a Poisson process. Under some mild conditions, we obtain a necessary and sufficient condition for the equivalence of dynamic and static asset allocations. In addition, we provide a simple sufficient condition for the equivalence.

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Simple tail index estimation for dependent and heterogeneous data with missing values

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Abstract. Financial returns are known to be nonnormal and tend to have fat-tailed distribution. Also, the dependence of large values in a stochastic process is an important topic in risk, insurance and finance. In the presence of missing values, we deal with the asymptotic properties of a simple "median" estimator of the tail index based on random variables with the heavy-tailed distribution function and certain dependence among the extremes. Weak consistency and asymptotic normality of the proposed estimator are established. The estimator is a special case of a well-known estimator defined in Bacro and Brito [*Statistics & Decisions* **3** (1993) 133–143]. The advantage of the estimator is its robustness against deviations and compared to Hill's, it is less affected by the fluctuations related to the maximum of the sample or by the presence of outliers. Several examples are analyzed in order to support the proofs.

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