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A Message from the President

by Christian Robert
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Dear ISBA Members, welcome to the new issue of the ISBA Bulletin, whose contents are getting richer and more diverse with each issue. I invite you to not only go over all the articles in the Bulletin but also to think hard about how to contribute yourself to the next one! More broadly, perhaps you can suggest new directions for articles. As mentioned by Peter Green in his penultimate message, this year is quite exciting in terms of travelling all around the world to ISBA meetings! I have attended two such meetings so far and my excitement is still at its highest! First, the MCMski meeting in Bormio was superb, both for the mix of theoretical and methodological talks and for the ultimately efficient organisation of the meeting: the snow itself was of the highest quality and we all managed to get home with no broken limbs! A major thanks to Antonietta Mira for taking such committed care of the meeting. Last month I also attended the 9th EBEB (encontros brasileiros de estatìstica bayesiana) meeting in Maresias, near Säo Paulo, that was organised by ISBrA, the Brazilian chapter of ISBA. This meeting gave me the wonderful opportunity to meet the Brazilian Bayesian community and to discover how active, how lively, and how diverse it is. The quality and the range of communications during this meeting were astounding, with an incredible proportion of enthusiastic students engaged in Bayesian statistics. (As a bonus, this meeting kept with the tradition of Bayesian meetings at the seaside, by picking an idyllic location on the Säo Paulo coastline.) *Continue in page* 2.

A Message from the Editor

by Raphael Gottardo
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Once again it's time for me to prepare a new issue of the bulletin. In this March issue, you will find many interesting articles including a nice article in the Bayesian History section on the evolution of Bayesian statistics in Korea. Tim and myself are trying to get a world tour on Bayesian history, so if you feel like you could contribute for one or even more than one country please send Tim or myself an email (see contact information on the last page). In addition to this, you will find the usual software review, application section, bibliography and news from the world. Speaking of news from the world, you will see that a few Bayesian events are scheduled to happen in beautiful British Columbia. ▲

In this issue

WORDS FROM THE PRESIDENT, *Continued from page 1.* As my first glimpse of a national ISBA chapter, this was a highly rewarding moment and I strongly encourage other national chapters to emerge in the near future. There are only five declared (national) chapters of ISBA at the moment but new chapters and sections can be created at any time, either on a national or on a thematic basis. Check on the ISBA website for more details. The World ISBA 2008 meeting in Hamilton is getting nearer and I encourage everyone to check on the conference website to see the diversity and the quality of the meeting emerging more and more clearly. I understand that distance and cost are two possible deterrents against attending ISBA 2008 but take yet another look at the site, one at the programme and one at the location, and think again! ISBA 2004 in Valparaiso sounded a bit too far at the time but those of us who attended this meeting came back with loads of experience and openings. In addition, remember that world meetings only occur once every four years! As a final word, I want to gratefully thank all of you that contribute, one way or another, to the life and development of ISBA. In particular, all the members involved in the various committees are essential to the success of our society. Lastly, many thanks to Peter Green for his decisive actions over the past year. ▲

ANNOTATED BIBLIOGRAPHY

ADAPTIVE MONTE CARLO METHODS

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Monte Carlo methods have profoundly changed the practice of Bayesian statistics over the last 15-20 years and are now widely accepted as one of the standard tools available to the statistician in order to help carry out inference. As attested by the search results for the term "Monte Carlo course" on the Web, they now form part of the undergraduate curriculum offered at numerous universities worldwide. Despite their numerous successes, these methods can be notoriously delicate to use: difficulties range from (a) the design of mathematically correct algorithms (it seems to be one of their main and unfortunate properties that these methods allow for very rapid contributions to the already very large collection of Monte Carlo howlers) (b) the implemention of efficient and reliable algorithms whose convergence can be observed in one's lifetime (c) the debugging of algorithms that produce a (pseudo-)random output.

It is therefore natural to wonder if computers can assist the Monte Carlo user in surmounting these difficulties, in particular (b). Indeed these algorithms require the choice of various tuning parameters in order to optimise their performance. It is the aim of the area of adaptive Monte Carlo methods to develop algorithms implementable on computers that optimise the performance of standard Monte Carlo methods, or at least a substantial proportion of their routinely used components. It is indeed probably illusory to aim for an all purpose Monte Carlo black-box due to the variety of potential applications

The aim of the annotated section is to provide a snapshot of the current literature on adaptive Monte Carlo relevant to Bayesian inference. This excludes some very interesting contributions such as 29. These, however, are well worth reading and are included in the final section, as citations only.

Papers dedicated to adaptive MCMC algorithms form the bulk of the papers included below, although one should not overlook adaptation in the context of population Monte Carlo algorithms (in the sense of 22) and sequential Monte Carlo samplers.

Annotated papers

1. Geyer, C. J. and E. A. Thompson. "Annealing Markov chain Monte Carlo with applications to ancestral inference", *Journal of the American Statistical Association*, vol. 90, no. 431, pp. 909–920, 1995.
   Although the paper focuses mainly on the idea of simulated tempering, it is suggested to use the Robbins-Monro algorithm in order to estimate, on the run, the unknown normalising constants required to imple-

ment the algorithm. Probably one of the earliest adaptive MCMC algorithms.

2. Ramponi, A. "Stochastic adaptive selection of weights in the simulated tempering algorithm," *Journal of the Italian Statistical Society*, vol. 7, no. 1, pp. 27–55, 1998.
The paper is dedicated to the theoretical analysis of the convergence properties of the algorithm suggested in 1, albeit in a restricted setup.

3. Holden, L. "Adaptive chains," *Technical Report - Norwegian Computing Center*, 1998.
One of the earliest contributions to the area of adaptive MCMC algorithms. No systematic approach to the optimisation of MCMC is suggested, but theoretical developments are provided that justify the convergence of the marginals of the process to the correct distribution. One assumption used is rather restrictive (it probably only applies to the independent Metropolis-Hastings algorithm) but can be easily removed.

4. Gilks, W. R., G. O. Roberts, and S. K. Sahu. "Adaptive Markov chain Monte Carlo through regeneration,"*Journal of the American Statistical Association* vol. 93, no. 443, pp. 1045–1054, 1998.
It is suggested to perform adaptation of MCMC algorithms at regeneration times, which avoids the problem of potential loss of ergodicity encountered with other techniques. It also allows for non-vanishing adaptation. The difficulty in practice is of course the efficient identification of regeneration times. The technique is applied to the optimisation of the expected acceptance probability.

5. Haario, H., E. Saksman, and J. Tamminen. "Adaptive proposal distribution for random walk Metropolis algorithm,"*Computational Statistics*, vol. 14, no. 3, pp. 375–395, 1999.
It is suggested to adapt the covariance matrix of the normal proposal distribution feeding a random walk Metropolis algorithm by learning the covariance matrix of the target distribution while running the algorithm. It is observed experimentally that without vanishing adaptation the samples produced do not result in consistent estimates of the quantities of interest.

6. Haario, H., E. Saksman, and J. Tamminen. "An Adaptive Metropolis Algorithm", *Bernoulli*, vol. 7, no. 2, pp. 223–242, 2001.
The algorithm proposed in 6 is studied theoretically in the case where adaptation is vanishing with the iterations. The paper contains the first proof, in this context, of the consistency of estimates built from the samples produced by the chain, in the form of a strong law of large numbers. The state-space is assumed to be bounded.

7. Laskey, K. B., and J. Myers. "Population Markov Chain Monte Carlo,"*Machine Learning*, vol. 50, no. 1-2, pp. 175–196, 2003.
Proposes to consider a population of MCMC updates whose proposal distribution(s) depend(s) on the whole population of samples, but no accumulation of information along the iterations is considered.

8. Andrieu, C., and C. P. Robert. "Controlled MCMC for optimal sampling," *Technical Report 0125 - Cahiers de Mathématiques du Ceremade, Université Paris-Dauphine*, 2001.
In this paper it is realised that 1 and 6 are particular instances of the standard Robbins-Monro recursion with Markovian dynamic (see 30). The paper identifies a general class of useful criteria which can be similarly optimised, such as the expected acceptance probability of the Metropolis algorithm.

9. Hastie, D. I. "Towards Automatic Reversible Jump Markov Chain Monte Carlo," *PhD thesis Bristol University*, March 2005.
The thesis contains some interesting and pragmatic contributions to the development of generic code for reversible jump MCMC algorithms. The Automix sampler is applied with success to various problems and its performance compared to that of algorithms especially developed for these applications.

10. Atchadé, Y. F. and J. S. Rosenthal. "On Adaptive Markov Chain Monte Carlo Algorithms," *Bernoulli* vol. 11, no. 5, pp. 815–828, 2005.
The paper revisits the proof of 6 and extends the result to the case where the state-space is unbounded, but the optimised parameter is still assumed to live in a bounded space, possibly by projection on

a fixed and predetermined set. An application to the optimisation of the expected acceptance probability is presented.

11. Andrieu, C., É. Moulines, and P. Priouret. "Stability of stochastic approximation under verifiable conditions,"*SIAM Journal on Control and Optimisation*, vol. 44, no. 1, pp. 283–312, 2005.
A general theory for the stability of the Robbins-Monro with Markovian dynamic is developed for an algorithm with adapted truncation sets. It is shown that the tail of the distribution of the number of reprojections decays super-exponentially. The theory is applied to the AM algorithm of 6 and does not necessitate any boundedness assumption either on the parameter or the state-space considered.

12. Andrieu, C., and É. Moulines. "On the ergodicity properties of some adaptive MCMC algorithms," *Annals of Applied Probability*, vol. 16, no. 3, pp. 1462–1505, 2006.
The paper focuses on the ergodicity properties of controlled MCMC in the situation where no boundedness assumption is made. Various estimates of the rate of convergence of such algorithms are provided (in the form of weak and strong laws of large numbers) that do not require the assumption that the optimised parameter is converging. The results are applied to the AM algorithm, but also an independent Metropolis-Hastings algorithm with a mixture from the exponential family as the proposal distribution. The mixture is fitted by minimising the Kullback-Leibler divergence and it is shown how an EM algorithm can be implemented in order to optimise this divergence. Finally a central limit theorem is proved, which seems to require the convergence of the parameter of interest.

13. Atchadé, Y. F. and J. S. Liu. "The Wang-Landau algorithm in general state spaces: applications and convergence analysis," *Technical Report - University of Michigan*, 2004.
The paper revisits the popular Wang-Landau algorithm from physics, reinterpreting it in the context of controlled MCMC 8 as well as providing a theoretical study. The algorithm is applied to reversible jump MCMC algorithms.

14. Haario, H., E. Saksman, and J. Tamminen. Componentwise adaptation for high. dimensional MCMC. *Computational Statistics*, vol. 20, no. 2, pp. 265–274, 2005.
It is proposed to extend the original AM algorithm 6 to a mixture of componentwise AM algorithms for high dimensional scenarios.

15. Nott, D. J., and R. Kohn., "Adaptive sampling for Bayesian variable selection," *Biometrika*, vol. 92, no. 4, pp. 747–763, 2005.
Proposes an algorithm for improved sampling in variable selection. The algorithm is suited for "unambiguous" scenarios where the marginal probability distributions of the indicator variables are either close to zero or one. The algorithm estimates the covariance matrix of the indicator variables and proposes updates "one variable at a time". A theoretical results is suggested that relies on the strong assumption of 3.

16. Atchadé, Y. F. "An adaptive version for the Metropolis adjusted Langevin algorithm with a truncated drift," *Methodology and Computation in Applied Probability,* vol. 8, pp. 235–254, 2006.
Shows how it is possible to automatically scale the Metropolis-Hastings adjusted Langevin algorithm using controlled MCMC. A theoretical study is carried out.

17. Roberts, G. O., and J. S. Rosenthal. "Coupling and ergodicity of adaptive MCMC," *Journal of Applied Probability,* vol 44, no. 2, pp. 458–475, 2007.
Proposes some proofs of convergence for controlled MCMC under conditions different from 6, 12 and 10. The underlying boundedness condition on the parameter is part of the assumptions and somewhat weaker results than in previous works are proved. The paper contains numerous interesting counterexamples. See also 27.

18. Andrieu, C., and Y. F. Atchadé. "On the efficiency of adaptive MCMC algorithms," *Electronic Communications In Probability*, vol. 12, pp. 336-349, 2007.
A form of coupling different from that exploited in 17 is used in order to study the convergence properties of controlled MCMC algorithms. Novel estimates of the rate of convergence of the optimised parameter are proposed.

19. Bédard M., D. A. S. Fraser, and A. Wong, "Higher accuracy for Bayesian and frequentist inference: Large sample theory for small sample likelihood, *Statistical Science*, vol. 22, no. 3, pp. 301–21, 2007.
Although the emphasis of the paper is not on adaptive MCMC algorithms, it is suggested to make the proposal distribution of the standard Metropolis-Hastings algorithm depend in a non-standard parametric way on the current state of the chain.

20. Roberts, G. O. and J. S. Rosenthal. "Examples of adaptive MCMC," *Technical Report - University of Toronto*, 2006.
Presents a thorough evaluation of various adaptive MCMC algorithms in very interesting high-dimensional scenarios. A section is dedicated to the optimisation of ideas similar to those in 19, i.e. localisation of the proposal distribution through a (non-standard) parametric dependence of the the tuning parameters of the proposal distribution on the current state of the Markov chain.

21. Giordani, P. and R. Kohn. "Efficient Bayesian inference for multiple change-point and mixture innovation models," *Sveriges Riksbank Working Paper*, no. 196, 2006.
Proposes an adaptive independent Metropolis-Hastings algorithm in the spirit of 12. An interesting contribution is the use of a "fast" K-mean algorithm in order to make the procedure robust. The algorithm is applied to two interesting scenarios.

22. Cappé, O., R. Douc, A. Gullin, J.-M. Marin, and C. P. Robert. "Adaptive importance sampling in general mixture classes," *preprint* 2007.
Not an MCMC algorithm, but an iterative importance sampling algorithm where the instrumental distribution used is fitted iteratively by minimising the Kullback-Leibler divergence as in 12 and using an EM algorithm.

23. Andrieu, C. and J. Thoms. "An overview of controlled MCMC", *Technical Report - University of Bristol*, 2008.
Contains a review of the area as well as a substantial number of novel algorithms.

Additional Papers

24. Andrieu, C. Discussion of 39 (December 2003), *Journal of the Royal Statistical Society, Series B*, vol. 66, no. 3, pp. 497–813, 2004.

25. Andrieu, C. and V. B. Tadić. "The boundedness issue for controlled MCMC algorithms,"*Technical Report - University of Bristol*, 2007.

26. Andrieu, C., A. Jasra, P. del Moral, and A. Doucet. "A Note on the Convergence of the Equi-Energy Sampler," *Stochastic Analysis and Applications*, vol. 26, pp. 298-312, 2008.

27. Yang, C., "On The Weak Law Of Large Numbers For Unbounded Functions," *Technical Report - University of Toronto*, 2008.

28. Yang, C., "Recurrent and Ergodic Properties of Adaptive MCMC," *Technical Report - University of Toronto*, 2008.

29. Baggerly, K., D. Cox, C. Kollman, and R Picard. "Adaptive importance sampling on discrete Markov chains" *Annals of Applied Probability*, vol. 9, no. 2, pp. 391–412, 1999.

30. Benveniste, A, M. Métivier, and P. Priouret. *Adaptive Algorithms and Stochastic Approximations*, Springer-Verlag 1990.

31. Chauveau, D. and P. Vandekerkhove. "Improving Convergence of the Hastings-Metropolis Algorithm with an Adaptive Proposal", *Scandinavian Journal of Statistics*, vol. 29, no. 1, pp. 13-29.

32. Erland S. "On Adaptivity and Eigen-Decompositions of Markov Chains", *PhD thesis Norwegian University of Science and Technology*, 2003.

33. Gåsemyr, J. "On an Adaptive Metropolis-Hastings Algorithm with Independent Proposal", *Scandinavian Journal of Statistics*, vol. 30, no. 1, pp. 159-173, 2003.

34. Sahu, S. K. and A. A. Zhigljavsky. "Adaptation for Self Regenerative MCMC", *Bernoulli*, vol. 9, no. 3, pp. 395–422, 2003.

35. Gåsemyr J., B. Natvig and C. S. Nygård. "An Application of Adaptive Independent Chain Metropolis–Hastings Algorithms in

Bayesian Hazard Rate Estimation," *Methodology and Computing in Applied Probability*, vol. 6, no. 3, pp. 293-302, 2004.

36. Pasarica, C. and A. Gelman. "Adaptively scaling the Metropolis algorithm using the average squared jumped distance," *Technical Report - Department of Statistics, Columbia University*, 2003.

37. Gilks, W. R., G. O. Roberts, and E. I. George. "Adaptive Direction Sampling," *The Statistician* vol. 43, pp. 179-189, 1994.

38. Haario, H., M. Laine, A. Mira, and E. Saksman. "DRAM: Efficient adaptive MCMC," *Statistics and Computing*, vol. 16, no. 4, pp. 339-354, 2006.

39. Haario, H., M. Laine, M. Lehtinen, and E. Saksman. "Markov chain Monte Carlo methods for high dimensional inversion in remote sensing," *Journal of the Royal Statistical Society Series B*, vol. 66, no. 3, pp. 591–607, 2004.

40. Holden, H., S. Sannan, H. H. Soleng, and O. J. Arntzen. "History matching using adaptive chains," *Technical Report - Norwegian Computing Center*, 2002.

41. Sims, C. A., Adaptive Metropolis-Hastings algorithm or Monte Carlo kernel estimation, *Technical Report - Princeton University*, 1998.

BAYESIAN HISTORY

History of the Bayesian society in Korea

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When I was asked to write a short history of the Bayesian society in Korea, I became very excited. Even though I majored in statistics as an undergraduate in Korea, the only exposure I had to the "Bayesian world" was a special-topics course in Bayesian statistics taught by Youn-Shik Chung at Pusan National University. And from this, the only memory I had of Bayesian statistics was the terms "prior" and "posterior". Then, I came to Texas A&M University for graduate studies and (proudly) became a Bayesian. Thus, this is a great opportunity for me to learn about Korea's Bayesian society and, in doing so, look back to my undergraduate years, and study individuals who have been dedicated to research in this field.

However, the search process has not been as easy as I had expected, mainly because I am currently in the United States, and there is a limited amount of information on the Internet. My first attempt was to search for Bayesian history on the website of *The Korean Society of Bayesian Statistics (KSBS)* (http://stat.pusan.ac.kr/~yschung/Bayesian/index.htm). I found that prior to the 1990s, there were not many Bayesian statisticians in Korea. However, many Bayesian statisticians returned to Korea after receiving their degrees throughout the world and decided to meet together to enhance their research in Bayesian statistics. Their first meeting took place at Choong-Nam National University in January 1996. After that, on an irregular basis, Bayesian researchers presented their work under the Bayesian section at regular spring and fall Korean Statistics Society conferences. The KSBS was formally established in February 1999 at a meeting at Dong-Kuk University, and it became an official subsection of the Korean Statistical Society in June 2000. Currently, there are about 40 members listed in the section, and they have regular conferences in February and August. The current chair of the KSBS is Professor Byung-Hui Kim of Han-Yang University. Unfortunately, the KSBS has been not very active in recent years.

After doing this research on the history of the KSBS, I wondered how Bayesian statistics research had grown in Korea. I found one paper addressing this topic: "The Past, Present, and Future of Bayesian Statistics" by Kim, YD, Kim, HJ, Oh, MS, Oh, HS, and Chung, YS, from a 2001 issue of the *Journal of the Korean Statistical Society (JKSS)*. Since the article was written in Korean, I translated part of it. The authors summarized what Bayesian statistics researchers have done, where they stand currently, and where they are headed in the future. In the past, Bayesian statistics was not actively developed; before the 90s, only about 8.5% of the articles in the top three Korean statistical journals (*Journal of the Korean Statistical Society, The Korean Journal of Applied Statistics (KJAS)*, and *The Korean Communications in Statistics*) were Bayesian-related (9% for *JKSS*, 6.5% for *KJAS*, and 8% for *Communicat ions*). However, the number of Bayesian papers has increased almost two-fold since the mid 1990's. This implies an increase in the number of Bayesian statisticians in Korea as well as an upswing in non-Bayesian statisticians' adaptations of Bayesian methods-a finding related to the introduction of advanced MCMC computation.

As a continued to research, my curiosity grew stronger. I dove into the Internet and frantically searched for the first (and the 2nd, and so on) Bayesian paper in *JKSS*. I Googled the archives of *JKSS*, and found the very first Bayesian paper:

"On the Bayesian Sequential estimation problem in k-parameter exponential family" by Yoon, BC, and Kim, JJ (1980, *JKSS*). In this paper, the Bayesian sequential estimation problem for k-parameter exponential families is considered using a loss function related to the Fisher information. Tractable expressions for the Bayes estimator and the posterior expected loss are presented, and the myopic, or one-step-ahead, stopping rule is defined.

The following are some Bayesian papers released from the early 80's to the early 90's. Research topics include decision rules and empirical Bayes estimation:

1. "An empirical Bayes estimation of multivariate normal mean vectors" by Kim, HJ (1986, *JKSS*)

2. "Admissibility of some stepwise Bayes estimators" by Kim, BH (1987, *JKSS*)

3. "A study on the Bayesian approach to outliers and influential observations in regression models" by Youn, BH (1987, *KJAS*).

4. "Empirical Bayesian multiple comparisons with the best" by Kim, WC, and Hwang, HT (1991, *JKSS*)

5. "Bayesian ratio estimation in finite populations" by Lee, SH, Park, NH, and Choi, JS (1992, *KJAS*)

Just like world-wide Bayesian statistics, improvements in Korean Bayesian statistics occurred right after advanced computation techniques were introduced; since 1994, there has been tremendous development in Bayesian methods. Papers written by Hea Jung Kim (Dong-Kuk University), Man Suk Oh (E-Hwa Woman's University), Dal-Ho Kim (Kyung-Buk National University), and Youn Shik Chung (Pusan National University), among many others, described new Bayesian methodology in different statistical models. For example, these include "Non-parametric estimation of mean residual life function under random censorship" (Park, BK, Sohn, JK, and Lee, SB, 1993, *JKSS*); "Bayesian analysis of the randomized response model: A Gibbs sampling approach" (Oh, MS, 1994, *JKSS*); "Sampling-based approach to Bayesian analysis of the binary regression model with incomplete data" (Chung, YS, 1997, *JKSS*); "Robust Bayes and empirical Bayes analysis in finite population sampling with auxiliary information" (Kim, DH, 1998, *JKSS*); and "A Bayesian variable selection method for binary response probit regression" (Kim, HJ, 1999, *JKSS*). I was also able to find many other papers written by Kim, HJ in the late 90's. In the early 2000's, research papers on non-parametric Bayesian methods came to the surface; Yong Dai Kim and Jae Yong Lee (Seoul National University) added more-lively research to Bayesian Statistics in Korea.

Overall, I enjoyed learning the history of Bayesian statistics and society in Korea; I am proud of Korea's short, but very active, Bayesian research history. I dream that an ISBA international meeting will be held in Korea in the near future, and I hope to see further statistical research advances come out of my home country.

APPLICATIONS

Rank likelihood estimation for continuous and discrete data

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Consider the semiparametric regression model

$$\begin{aligned} z_i &= \beta^T x_i + \epsilon_i \\ y_i &= g(z_i), \end{aligned}$$

where β is a vector of regression coefficients and g is an unknown non-decreasing function. In many situations, interest lies in the association between y and x (represented by β), but not in the measurement scale of y (represented by g). A rank likelihood is a type of semiparametric marginal likelihood function that is useful for these situations, as it depends on β only and not on the nuisance parameter g. While procedures for obtaining MLEs based on the rank likelihood are complicated, it turns out that the associated Markov chain Monte Carlo procedures for Bayesian inference are extremely simple, often requiring just a few additional lines of R-code beyond those required by ordinary methods. In this short article I motivate the rank likelihood in the context of regression and copula estimation, illustrate the methodology with an example and provide computer code to implement the necessary MCMC algorithm.

Motivation

While the normal model serves us well when describing the variability of the sample mean, many of us find it lacking as a realistic sampling model for much else. I became acutely aware of this the first time I taught estimation for normal populations to a group of social science graduate students. It must have taken me the better part of a day to find an interesting example of a real-life social science dataset that included a variable anywhere close to being normally distributed, and in the end it still needed a log transformation.

The students in my class were used to working with survey data that included variables such as sex, education level, attitudes and income: variables that we may consider binary, ordinal and continuous. Often the scale on which these variables are measured is arbitrary - income, age and attitude variables are often binned into ordered categories, the number of which varies from survey to survey. Furthermore, interest in these variables typically lies not in their univariate marginal distributions, but rather in their multivariate associations: Is the relationship between two variables increasing, decreasing or zero? Is the relationship monotonic or quadratic? What happens if we "account" for a third variable?

Transformation models

Most model-based approaches to answering such questions have one of two undesirable features: either they rely on the observed data being normally distributed, or they require a lot of effort to simultaneously estimate the marginal distributions along with the association parameters. Fortunately, an interesting alternative to these approaches exists: Consider the following regression model for the conditional distribution of $y_1, \ldots, y_n$ given $x_1, \ldots, x_n$:

$$\begin{aligned} \epsilon_1, \ldots, \epsilon_n &\sim \text{i.i.d. normal}(0,1) \\ z_i &= \beta^T x_i + \epsilon_i \\ y_i &= g(z_i) \end{aligned}$$

The unknown parameters in this system are β and g, the latter of which can be assumed to be a nondecreasing function that describes the marginal distribution of y. If y is discrete with a finite number of levels then the above model is an ordered probit model and g is determined by its points of discontinuity. If y is continuous then g is some unknown increasing function. In either case, a full Bayesian analysis would require prior distributions for β and g, even if only β is of interest. However, there is information in the data about β that doesn't depend on the nuisance parameter g: We don't observe the z_i's directly, but since g is monotone we do know the *order* of the z_i's. In particular, we know that z lies in the set

$$R(y) = \{z \in \mathbb{R}^n : z_i < z_j \text{ if } y_i < y_j\}. \quad (1)$$

Note that since the distribution of z doesn't depend on g, the probability that $z \in R(y)$ for a given y also doesn't depend on the nuisance parameter g:

$$\begin{aligned} p(z \in R(y)|\beta, g) &= \int_{R(y)} \prod_{i=1}^{n} \phi(z_i - \beta^T x_i)\, dz_i \\ &= p(z \in R(y)|\beta) \end{aligned}$$

For continuous data, $p(z \in R(y)|\beta)$ is the same as the probability of the observed ranks. Taken as a function of β, this forms the "rank likelihood," introduced in the regression context by Pettitt (1982). The rank likelihood is a type of marginal likelihood that depends on the parameter of interest β and not on the nuisance parameter. Doksum (1987) has studied this type of likelihood for general transformation models, which includes the proportional hazards model as a special case, and Bickel and Ritov (1997) study the asymptotic properties of the rank likelihood estimator of β. For discrete data, the information contained in $\{z \in R(y)\}$ is less than that contained in the ranks, because the former does not contain information about ties. However, $p(z \in R(y)|\beta)$ still provides a marginal likelihood for β which doesn't depend on the nuisance parameter g.

Rank likelihood estimation

Given the observed value y_{obs} of y, the rank likelihood estimate of β is obtained by maximizing $p(z \in R(y_{\text{obs}})|\beta)$ as a function of β. The fact that the likelihood involves a complicated integral makes obtaining the MLE very difficult, and existing estimation methods offer only approximate MLEs. This has probably been the greatest obstacle to the widespread adoption of the rank likelihood approach to regression. However, it turns out that Bayesian estimation using the rank likelihood is comparatively straightforward. Taking the event $\{z \in R(y_{\text{obs}}\}$ as our observed information, we can obtain samples of $\{z, \beta\}$ conditional on this information via iterative Gibbs sampling. The relevant full conditional distributions are quite simple:

$p(\beta|z, z \in R(y_{\text{obs}})) = p(\beta|z)$ is a multivariate normal distribution (assuming $p(\beta)$ is multivariate normal).

$p(z_i|\beta, z_{-i}, z \in R(y_{\text{obs}}))$ is a normal density constrained to the interval

$$\max\{z_j : y_j < y_i\} < z_i < \min\{z_j : y_i < y_j\}.$$

Example

Let's take a look at how rank likelihood estimation can be implemented in R in the context of an example. The 1996 General Social Survey gathered a wide variety of information on the adult U.S. population, including each survey respondent's sex, their self-reported frequency of religious prayer (on a six-level ordinal scale), and the number of items correct out of 10 on a short vocabulary test. We'll estimate the parameters in a regression model for y_i=prayer as a function of $x_{i,1}$ = sex of respondent (0-1 indicator of being female) and $x_{i,2}$ = vocabulary score. Our model is

$$\begin{aligned} z_i &= \beta_1 x_{i,1} + \beta_2 x_{i,2} + \beta_{12} x_{i,1} x_{i,2} + \epsilon_i \\ y_i &= g(z_i) \end{aligned}$$

From these data and this model we hope to learn if the relationship between prayer and vocabulary score is positive, negative or zero, and whether or not the relationship is different for men and women. Letting $(\mathtt{y}, \mathtt{X})$ be R-objects containing the data, R-code for the estimation procedure described above is as follows:

```
##### data setup and starting values
n<-dim(X)[1] ; p<-dim(X)[2]
ranks<-match(y,sort(unique(y)))
uranks<-sort(unique(ranks))
z<-qnorm(rank(y,ties.method="random")/(n+1))
b<-matrix(0,p,1)
#####

for(s in 1:S)
{
  ##### update z
  mu<-X%*%b
  for(r in sample(uranks))
  {
    ir<-(1:n)[ranks==r]
    lb<-max(z[ranks<r]) ; ub<-min(z[r<ranks])
    z[ir]<-qnorm(
    runif( length(ir),
    pnorm(lb,mu[ir],1),
    pnorm(ub,mu[ir],1) ),mu[ir],1)
  }
  #####

  ##### update b
  V<-solve ( t(X)%*%X +diag(1,nrow=p) )
  E<-V%*%( t(X)%*%z )
```

```
  b<-chol(V)%*%rnorm(p) + E
  #####
}
```

Data and code for this example are available at www.stat.washington.edu/hoff/ISBAexample. In practice, the mixing of the Markov chain is improved if the columns of X are centered to have mean zero.

I ran this algorithm for 25,000 iterations, saving the value of β every 25th iteration leaving 1000 samples with which to estimate the posterior distribution. Some posterior quantiles for the regression parameters are as follows:

	2.5%	50%	97.5%
β_1	0.45	0.88	1.29
β_2	-0.06	-0.02	0.01
β_{12}	-0.10	-0.08	-0.05

These results indicate that the relationship between prayer and vocabulary score differs between men and women: The (2.5,50,97.5)% quantiles for the sex specific slope parameters are (-.13,-.10, -.06) for women and (-.06, -.02, .01) for men, indicating that women's prayer rate decreases more rapidly as a function of vocabulary than does that of the men. This is shown graphically in the figure, which plots the posterior mean regression lines for both sexes, along with a single posterior sample of z (the last sample from the Markov chain).

Copula estimation

In the above example all three variables were sampled. In such situations it may be desirable to estimate the joint dependence among all three variables. This can be accomplished with the Gaussian copula model:

$$\begin{aligned} z_i = (z_{i,1}, \dots, z_{i,p}) &\sim \text{multivariate normal}(0, \Sigma) \\ y_{i,j} &= g_j(z_{i,j}),\ j \in \{1, \dots, p\} \end{aligned}$$

As described in Hoff (2007), estimation of Σ using the rank likelihood can be implemented by conditioning on the event

$$R(y) = \{z_1, \dots, z_n : z_{i_1,j} < z_{i_2,j} \text{ if } y_{i_1,j} < y_{i_2,j}\}.$$

This estimation procedure does not require modeling the univariate marginal distributions, and is applicable for mixed discrete and continuous data.

Summary

By only using part of the observed information, rank likelihoods allow for estimation of dependence parameters without having to deal with high-dimensional nuisance parameters. Distributions of the dependence parameters, conditional on the partial information, are easily approximated via Gibbs sampling. Besides regression and copula estimate, there are undoubtedly a variety of other semiparametric inference problems that can be addressed by a combination of rank likelihood and Bayesian methodology.

References

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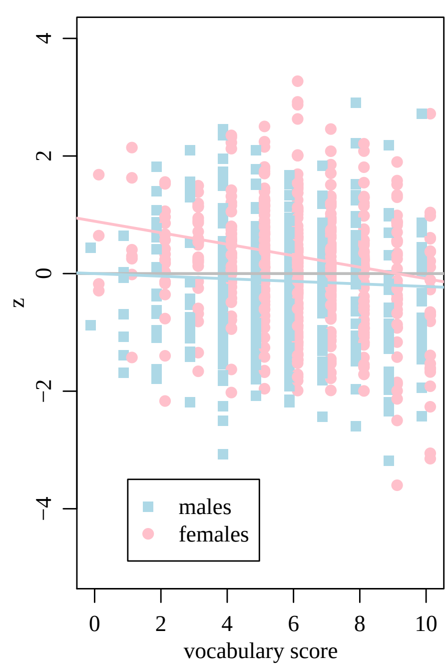

SOFTWARE HIGHLIGHT

BayesX – Bayesian Inference in Structured Additive Regression

by Thomas Kneib, Christiane Belitz, Andreas Brezger and Stefan Lang
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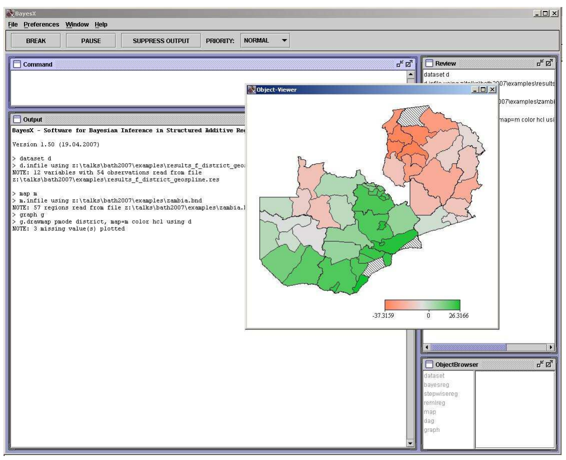

BayesX is a stand-alone software for estimating structured additive regression models. Structured additive regression provides a unifying framework for a large class of regression models including generalised additive mixed models, geoadditive models, and models with varying coefficients. In particular, it combines nonparametric, smooth effects of continuous covariates and time scales with spatial effects and random effects, allowing for considerable flexibility in the specification of regression models. Besides exponential family regression, BayesX also supports non-standard regression situations such as regression for categorical responses, hazard regression for continuous survival times, and continuous time multi-state models. Inference can be either empirically Bayesian yielding posterior mode estimates or fully Bayesian based on MCMC simulation. The best starting point for learning more about structured additive regression are [1] for a general overview and [2] for inference based on MCMC. Additional references and resources including worked tutorials as well as the installation routine of BayesX are available free of charge from

`http://www.statistik.lmu.de/~bayesx`

In its current version, BayesX only under the various versions of the Windows operating system. A Linux version is planned for the (not too near) future.

Model Components

Structured additive regression models can be build from arbitrary combinations of the following model terms:

- *Nonlinear effects* of continuous covariates can be estimated based on either penalised spline or random walk models.
- Autoregressive priors adapted from state space models yield flexible, time-varying *seasonal effects*.
- *Spatial effects* can be specified based on Gaussian Markov random fields, stationary Gaussian random fields (referred to as kriging in geostatistics) or bivariate penalised splines. Both georeferenced regional data as well as point-referenced data based on coordinates are supported.
- Bivariate Tensor product penalised splines yield flexible *interaction surfaces* between continuous covariates.
- *Varying coefficient models* with either continuous or spatial effect modifiers can be estimated. The latter case is also known as geographically weighted regression.
- Cluster-specific i.i.d. Gaussian *random intercepts and slopes*.

Types of Responses

BayesX allows to specify structured additive regression models for the following types of responses:

- *Univariate exponential family*: Supported response distributions are Gaussian, Poisson, Binomial, Gamma, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial.
- *Categorical responses with unordered responses*: BayesX supports multinomial logit and multinomial probit models. Effects of

both category-specific and globally-defined covariates can be estimated. Category-specific offsets or non-availability indicators can be defined to account for varying choice sets.

- *Categorical responses with ordered responses*: Ordinal as well as sequential models can be specified in combination with either the logit or probit link function. Effects can be requested to be category-specific or to be constant over the categories.

- *Continuous time survival models*: BayesX supports Cox-type hazard regression models with structured additive predictor for continuous time survival analysis. In contrast to the Cox model, the baseline hazard rate is estimated jointly with the remaining effects based on the full rather than the partial likelihood. Furthermore, both time-varying effects and time-varying covariates can be included in the predictor to overcome the proportional hazards property of the Cox model. Arbitrary combinations of right, left and interval censored as well as left truncated observations can be present in a data set.

- *Continuous time multi-state models*: Multi-state models form a general class for the analysis of the evolution of discrete phenomena in continuous time. Transition intensities between the discrete states are specified in an analogous way to the hazard rate in continuous time survival models.

Inferential Procedures

Estimation of regression models can be achieved based on two different inferential concepts: Markov chain Monte Carlo simulation techniques corresponding to full Bayesian inference and mixed model methodology corresponding to penalised likelihood or empirical Bayes inference. Both concepts have been implemented in separate regression objects:

MCMC simulation techniques (bayesreg objects). A fully Bayesian interpretation of structured additive regression models is obtained by specifying prior distributions for all unknown parameters. Bayesreg objects provide numerically efficient implementations of MCMC-schemes for different types of structured additive regression models. Suitable proposal densities have been developed based on iteratively weighted least squares proposals to obtain rapidly mixing, well-behaved sampling schemes without the need for manual tuning. The computational kernel of BayesX is implemented in C++ leading to fast execution, allowing for quite complex models even in combination with data sets with tens or hundreds of thousands of observations.

Mixed model based estimation (remlreg objects). An increasingly popular way to estimate semiparametric regression models is the representation of penalisation approaches as mixed models. Within BayesX this concept has been extended to structured additive regression models and several types of non-standard regression situations. The general idea is to take advantage of the close connection between penalty concepts and corresponding random effects distributions. The smoothing parameters of the penalties transform to variance components of the random effects and mixed model methodology can be applied to determine the restricted maximum likelihood estimates while the regression coefficients are obtained by penalised likelihood estimation. From a Bayesian perspective, this yields empirical Bayes / posterior mode estimates for the structured additive regression models. However, estimates can also merely be interpreted as penalised likelihood estimates from a frequentist perspective.

Note that parts of the functionality described in *Model Components* and *Types of Responses* may be available for one of the regression types only. For example, full Bayesian estimation does not support interval censored survival times while multinomial probit models can not be estimated based on mixed models. Details can be found in the reference manual available from the BayesX homepage.

Further Functionality

In addition to the estimation of structured additive regression models, BayesX provides some further functionality:

- *Handling and manipulation of data sets.* BayesX contains a growing number of functions for handling and manipulating data sets, e.g. for reading ASCII data sets, creating new variables, obtaining summary statistics etc.

- *Handling and manipulation of geographical maps.* BayesX is able to manipulate and draw geographical maps. The regions of the map may be colored according to some numerical characteristics.

- *Visualizing data*. BayesX provides functions for drawing scatter plots and geographical maps. A number of additional options are provided to customize the graphs according to the personal needs of the user.

References

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STUDENTS' CORNER

by Luke Bornn
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We start this issue's Students' Corner with an article by Mark Briers discussing taking your Bayesian training into industry. Following this we have two dissertation abstracts from recent graduates of the University of British Columbia. Many thanks to these contributors, and if you would like to submit an abstract or article, please don't hesitate to contact me.

Bayes in Industry

by Mark Briers
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The use of Bayesian statistics spreads across many industries and applications can be found in many places: in my day-to-day work, I have applied aspects of Bayesian analysis to automatic target recognition problems, tracking marine mammals, and e-mail spam filtering. In this article I would like to describe some of my experiences of where and how I have used Bayesian statistics in my career, what it is like to conduct research in a commercial environment, and hopefully convey the usefulness of a (Bayesian!) statistical background as we, as young researchers, embark upon careers outside of academia.

I joined QinetiQ (formerly the UK MOD's Defence Evaluation and Research Agency) in 2001 after finishing my undergraduate degree. The job vacancy was advertised on the UK's prospects.ac.uk website. Having never been to a "real" interview before, I was very nervous before the event. I had investigated the history of the organisation and completed several online practice psychometric tests but still felt unprepared. The interview felt like it went by very quickly (although it lasted a couple of hours). I was required to deliver a 20 minute presentation (on a subject of my choice) and answer many technical and business-like questions. In hindsight, my pre-interview research was adequate and I'm glad I spent some time preparing. I received a job offer two weeks after the interview, all that was left to do was to pass my final undergraduate exams...

QinetiQ develops and evaluates next generation defence and security technological solutions. My department is primarily interested in wide area surveillance, combining disparate information sources to produce an improved situational awareness picture. In other words (i.e. in English!), this means that we want to take the output of several sensors that are producing measurements relating to various aspects of the area to be protected, possibly incorporate human intelligence information, and create a single ("fused") unambiguous picture that can be presented to security personnel. This information also needs to be updated as time (and our knowledge of the world) evolves. The need to utilise Bayesian statistics in this context should be evident; we need to accurately quantify the uncertainty associated with the random phenomena of interest (the characteristics of potential hostile targets). Due to the severe non-linearities in the sensor models deployed, the conflicting nature of the information sources available, and the strong desire to utilise any expert information available, no matter what the form, a closed form solution to the sequential Bayesian recursion very rarely exists. Thus, the need to deploy advanced inference techniques, particularly Monte Carlo based, is key. The subject of my recent PhD, therefore, has been the development of improved Monte Carlo techniques for use in state-space models. Whilst my application focus may rest in the defence and security sector, a lot of the publications in the Monte Carlo methodology area (and Bayesian statistics in general) are not applied in this context. The benefits of this cross-discipline applicability of Bayesian methods are twofold: for the interests of my defence and security customers, I am able to utilise/extend/steal(!) ideas from other application domains to provide improved solutions to their problems. Secondly, from a personal point-of-view, I am being paid to learn about general Bayesian statistical techniques, which can only serve to improve my future career options.

As part of my position at QinetiQ, I was being paid to complete a PhD at Cambridge University (with generous support from the 1851 Royal Commission). Practically, this meant I spent approximately half of my time working directly on my PhD (physically based at the University), and the other half I had to work on relevant project work at QinetiQ (physically based at the company's offices). The difference between the two worlds could be very different - I was always the first person into the lab at uni (8.00am) and worst of all, I was expected to buy rounds of drinks for the other students as I was the only person earning a "decent" salary!! At university, I was able to spend time exploring my own ideas, I had time to spare to try things that were destined not to work, and so I was able to develop my problem solving skills. In the commercial world, however, such freedom is very rare; the customers expect the research to have evolved in the three month period between review meetings, project managers are paid to ensure that work is progressing, and many distractions are present (business strategy meetings, proposal writing, project control meetings, ...). Such constraints are not necessarily a bad thing; I remain very focused when working and I am constantly aware of what I need to achieve (and probably have a good idea of how I am going to arrive at the solution before I start to tackle the problem!). This quality would benefit many PhD students, not least at writing-up time! To ensure that the research gets utilised in real-life situations as quickly as possible, I'm also required to contribute to several software projects. This has seen me develop my programming design/implementation/testing skills, and has helped me to realise how difficult and complex the process actually is of turning an idea on a whiteboard into an end-user product.

A career in the commercial world using Bayesian statistics is very rewarding. The typical generality of Bayesian methods (and statistics in general) means that one is not necessarily tied to, and trained in, one niche area. The day-to-day focus that a commercial environment actually provides is invaluable in ensuring that tasks can be completed in a reasonable amount of time. Further, there is a certain satisfaction in actually seeing your idea (that started off life in R) being used in an actual product, especially if such a product is beneficial to humankind.

Dissertation Abstracts

Bayesian Adjustments for Measurement Error in Covariates with Special Reference to Logistic Regression Model: A Flexible Parametric Approach

by Shahadut Hossein
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PhD Supervisor: Paul Gustafson (UBC)

In many fields of statistical application the fundamental task is to quantify the association between some explanatory variables or covariates and a response or outcome variable through a suitable regression model. The accuracy of such quantification depends on how precisely we measure the relevant covariates. In many instances, we can not measure some of the covariates accurately. Rather, we can measure noisy versions of them. In statistical terminology this is known as measurement errors or errors in variables. Regression analyses based on noisy covariate measurements lead to biased and inaccurate inference about the true underlying response-covariate associations.

In this thesis we investigate some aspects of measurement error modeling in the case of a logistic regression model. We suggest a flexible parametric approach for adjusting the measurement error bias while estimating the response-covariate relationship through logistic regression

model. More specifically, we propose a flexible parametric distribution for modeling the true but unobserved exposure. We investigate the performance of the proposed flexible parametric approach in comparison with the other flexible parametric and nonparametric approaches through extensive simulation studies. We also compare the proposed method with the other competing methods with respect to a real-life data set. For inference and computational purpose, we use the Bayesian MCMC techniques. Though emphasis is put on the logistic regression model the proposed method is unified and is applicable to the other members of the generalized linear models, and other types of nonlinear regression models too. Finally, we develop a new computational technique to approximate the large sample bias that may arise due to exposure model misspecification in the estimation of the regression parameters in a measurement error scenario.

Combining Measurements With Deterministic Model Outputs: Predicting Ground-Level Ozone

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The main topic of this thesis is about combining model outputs from deterministic models with measurements from monitoring stations for air pollutants or other meteorological variables. We consider two different approaches to address this particular problem.

The first approach is by using the Bayesian Melding (BM) model proposed by Fuentes and Raftery (2005). We successfully implement this model and conduct several simulation studies to examine the performance of this model in different scenarios. We also apply the melding model to the ozone data to show the importance of using the Bayesian melding model to calibrate the model outputs. That is, to adjust the model outputs for the prediction of measurements. Due to the Bayesian framework of the melding model, we can extend it to incorporate other components such as ensemble models, reversible jump MCMC for variable selection.

However, the BM model is purely a spatial model and we generally have to deal with space-time dataset in practice. The deficiency of the BM approach leads us to a second approach, an alternative to the BM model, which is a linear mixed model (different from most linear mixed models, the random effects being spatially correlated) with temporally and spatially correlated residuals. We assume the spatial and temporal correlation are separable and use an AR process to model the temporal correlation. We also develop a multivariate version of this model.

Both the melding model and linear mixed model are Bayesian hierarchical models, which can better estimate the uncertainties of the estimates and predictions.

Simulation Methods for Bayesian Inference on Latent Variable Models

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Latent variable models are now very common in econometrics and statistics. The thesis deals with the use of latent variables in mixture modeling and time series analysis. The presence of unobservable components makes the inference process more difficult. Both maximum likelihood and Bayesian estimation require integration over a high dimensional space, of the likelihood function in the first case and of the posterior distribution in the latter. I follow a Bayesian inference framework. Its strong probabilistic basis allows dealing with very general latent variable models and introducing, in a natural way, the simulation methods into the inference process.

In the first part of the research I define a Bayesian state space representation for dynamic models with latent variables, introduce the related inference problems and describe how to use sequential Monte Carlo (SMC) methods. The first contribution of the thesis is a comparison in a Bayesian framework between some regularised particle filters with different kind of importance distributions.

I propose Markov-Switching Stochastic-Volatility (MSSV) models with a heavy-tail observable process. The Markov-switching process captures clustering effects and regimes-changing in volatility and correlations. Heavy-tail innovations account for extreme variations in the observed process. I follow a Bayesian approach and make use of SMC, in order to filter the state and estimate the parameters.

Another research contribution is the application of the MSSV models and the SMC method to the parameters and the latent volatilities estimation for the US business cycle and the stock market valuations. I also propose a new regularised SMC procedure, in which kernels with a multiple-bandwidth, are employed to move the particles. I give a proof of the convergence of the proposed regularised PF, verify the effectiveness of the algorithm on simulated data and provide an application to business cycle data.

In the last contribution of the thesis I suggest the use of α-stable mixtures in financial modelling, in order to account for skewness, heavy tails and multimodality of the financial returns. I follow a full Bayesian approach and propose an MCMC algorithm for estimating the parameters of α-stable mixtures.

NEWS FROM THE WORLD

Announcements

New Membership Partnership with IMS

The Institute of Mathematical Statistics (IMS) and ISBA are pleased to announce that ISBA members can join (or renew) with IMS at 25% off the regular IMS dues rate, and that IMS members can join (or renew) with ISBA at 25% off the regular ISBA dues rate. For example, ISBA members pay US$71 for a year's IMS membership. For all the IMS dues and subscription prices for individual members, see the IMS or (soon) ISBA join/renewal pages.

Events

Workshop on Bayesian Methods That Frequentists Should Know, College Park, Maryland, 30 Apr - 1 May, 2008.

The main purpose of the workshop is to assess the current state of usage of the Bayesian methodology in different disciplines and to discuss potential issues preventing the applications of the Bayesian methods. The workshop will highlight methods that have broad interest and appeal cutting across the Bayesian/Frequentist divide. The two-day Program will consist of six plenary sessions, a pair of general lectures (the Statistics Consortium Distinguished Lectures) in a special afternoon session on Wednesday, April 30, and a Poster Session to be held during a general Reception immediately following the general lecture session. The plenary sessions each consist of a 45 minute to 1 hour lecture with a formal discussion wherever possible, followed by floor discussion. The confirmed participants of the plenary sessions and general lectures are: James O. Berger (Duke University), Snigdhansu Chatterjee (University of Minnesota), Malay Ghosh (University of Florida, Gainesville), Stephen Fienberg (Carnegie Mellon University), Roderick J.A. Little (University of Michigan, Ann Arbor), Carl N. Morris (Harvard University), J.N.K. Rao (Carleton University) and Alan M. Zaslavsky (Harvard University). Posters that are related to the theme of the workshop will be accepted, subject to space constraints.

Please visit the workshop web site `http://www.jpsm.umd.edu/stat/workshop` for detailed information on the workshop, on the Statistics Consortium Distinguished Lectures, and on submission of abstracts for posters. There is no registration fee for attending the workshop, the Statistics Consortium Distinguished Lectures or the reception. We strongly request that you indicate your interest by completing the registration form, which can be downloaded from the website, and sending it to `statcons@math.umd.edu` or to: Eric Slud, Statistics Consortium, Mathematics Department, Mathematics Building, University of Maryland, College Park, MD 20742, USA, by March 15, 2008.

Summer Institute of Applied Statistics, Provo, Utah, 18-20 June, 2008.

The 33rd Annual Brigham Young University Summer Institute of Applied Statistics will be presented by Dr. Scott M. Berry, of Berry Consultants, and is entitled 'Bayesian Clinical Trials'. The course will describe recent Bayesian innovations in the design and analysis of clinical trials. For more information, please visit the website http://statistics.byu.edu/summer_institute/.

Bayesian Phylogeny Workshop, Budapest, Hungary, 25-29 June, 2008.

The workshop is organized by the Alfréd Rényi Institute of Mathematics and the University of Oxford. The goal of the conference is to give a comprehensive overview of Bayesian phylogeny and its widely used techniques like Markov chain Monte Carlo. Each day will be dedicated to a specific topic. The topics will be introduced by top-qualified researchers during the morning sessions, the afternoon sessions are devoted to discussions, software demos, tutorials and short presentations.

There is no registration fee for this workshop, however, registration is necessary. Proposals for short talks are welcome. One page abstracts can be submitted on the registration page. The deadline for submissions is 15th of May. For more information, please visit the website at http://www.renyi.hu/conferences/bp2008/.

Summer School on Bayesian Modeling and Computation, UBC, Vancouver, Canada, 14-18 Jul, 2008.

The summer school, sponsored by the PIMS Collaborative Research Group, will be a mix of theoretical and practical courses, taught by world experts in the field. It will be organized in modules (2x1.5h of lectures) over 5 days. Modules will include model selection, stochastic computation, MCMC, non parametric Bayes, introduction to WinBUGS and machine learning. The maximum number participants that will be accepted to the summer school is 40. As we except the number of applicants to exceed this number, students will be offered a place based on academic record. Registration fees will be covered by PIMS for all accepted participants. Accommodation expenses will also be covered by PIMS for out of town participants. For more information, please visit the website at http://www.stat.ubc.ca/~raph/BayesCRG/Activities/SummerSchool/SummerSchool.html.

World Meeting of the International Society for Bayesian Analysis, Hamilton Island, Australia, 21-25 Jul, 2008.

You are warmly invited to join us for the 9th World Meeting of the International Society for Bayesian Analysis (ISBA), to be held on Hamilton Island Australia in 2008. The ISBA conferences are held every two years, with every second one held jointly with the Valencia meetings. These conferences have become one of the premier events in Bayesian statistics. ISBA 2008 will broadly follow the tradition of these meetings, combining an excellent scientific programme that includes 5 keynote speakers, 90 oral presentations run over 3 parallel sessions and two poster evenings, with an active social schedule aimed at allowing delegates time to explore this beautiful location. For additional details go to the website, http://www.isba2008.sci.qut.edu.au/, or e-mail isba08@qut.edu.au.

Sample Surveys and Bayesian Statistics: Workshop and Conference, Southampton, UK, 26-29 Aug, 2008.

The aim of this meeting is to highlight the potential advantages of Bayesian methodology and discuss and illustrate its possible applications in diverse areas of sample survey design and inference. The meeting will begin with a 1.5 days workshop, given by Professor Malay Ghosh (University of Florida, U.S.) and Professor Rod Little (University of Michigan, U.S.). It will be followed by a 2.5 days conference, consisting of invited and contributed research and applied papers, and a special panel discussion. Information on registration to the workshop and conference and submission of abstracts of contributed papers can be found on the conference website www.s3ri.soton.ac.uk/ssbs08/.