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A MESSAGE FROM THE PRESIDENT

by Sylvia Richardson
ISBA President
sylvia.richardson@imperial.ac.uk

This year has been very productive for ISBA with a strong society engaged worldwide, the establishment of Sections to encourage diversity, many successful meetings (my personal highlight was the MCMski meeting in Bormio), and the launch of our electronic journal *Bayesian Analysis* under the stewardship of Rob Kass. Following on from the launch, a proposal to distribute paper copies under the umbrella of the IMS is under discussion by both Societies. Both the Bulletin and Bayesian Analysis are flagships for our Society and we are indebted to Rob Kass and Andrés Christen for their work on the editorial side.

This year has passed too quickly (don't they all?) and I look forward to carrying on working with our new President, Alan Gelfand, to advance some of the unfinished business, in particular concerning the arrangements for the upkeep of Bayes' grave. I have enjoyed working with the ISBA community and I would like to thank all members of the Board and of the Executive, in particular the past President Jim Berger and the treasurer Bruno Sansó, for being so responsive. I would also like to thank all of you who have accepted new responsibilities on both the prize committees and programme committees, and congratulate our new elected board members: Marilena Barbieri, Wes Johnson, Steve MacEachern and Jim Zideck, as well as our new President Elect Peter Green.

I wish you all a happy and successful year in 2006 and look forward to seeing you at our next ISBA 2006 conference in Valencia.▲

A MESSAGE FROM THE EDITOR

by J. Andrés Christen
jac@cimat.mx

The last issue of the year presents an assorted selection of interesting articles, from regular sections to a contribution from Tony O'Hagan; I hope you enjoy reading it as much as I did.

The treasurer of ISBA, Bruno Sansó, wishes to thank a donation to the Valencia 8 meeting (to be held next June) by BEST, LLC. We thank BEST, LLC, again for this generous donation.

Finally, please do not hesitate to send me any suggestions about articles that you may wish to see published in the Bulletin, or send me any free contribution you might feel is of general interest for the ISBA community. Taking the opportunity of this December issue, I wish you all a great and exiting Bayesian 2006, and also a terrific summer ... to all

our Bayesian friends in the southern hemisphere.



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ADVANCED MARKOV CHAIN MONTE CARLO METHODS

by Faming Liang

fliang@stat.tamu.edu

Markov chain Monte Carlo (MCMC) methods are rooted in the work of physicists such as Metropolis and von Neumann during the period 1945-1955 when they employed modern electronic computers for the simulation of some probabilistic problems in atomic bomb designs. After five decades of continual development, they have become the dominant methodology in the solution of many classes of computational problems of central importance to science and technology. The MCMC methods have numerous application areas such as Bayesian statistical inference, spin-glasses simulations, chip design, image processing, economics and finance, signal processing, machine learning, biological sequence analysis, phylogeny inference, protein structure prediction, microarray data analysis, among others.

In brief, a MCMC method simulates a Markov chain to draw samples proportionally (with respect to the invariant distribution) from each part of the sample space, and then conducts statistical inferences based on the samples drawn during the simulation process. The local trap phenomenon occurs when the energy function, or the negative log-posterior density function in Bayesian statistics, has multiple local minima separated by high energy barriers. In this situation the Markov chain will be trapped into a local energy minimum indefinitely. Consequently, the simulation process may fail to sample from the relevant parts of the sample space, and the quantities of interest can not be estimated correctly. Many applications of the MCMC methods, such as protein folding, combinatorial optimization, and spin-glasses, could be dramatically enhanced if we had better algorithms which allowed the process to avoid being trapped into local minima. Developing advanced MCMC methods that are immune to the local trap problem has long been considered as one of the most important research topics in scientific computing. A non-exhaustive list of the works in this direction is as follows.

- Berg, B.A. and Neuhaus, T. (1991). Multicanonical algorithms for 1st order phase-transitions. *Physics Letters B*, **267**, 249-253.

The authors propose the multicanonical algorithm which seeks to generate samples from a trial distribution under which the en-

ergy variable is approximately uniformly distributed, and propose an iterative procedure for constructing such a trial distribution.

- Chen, M.-H. and Schmeiser, B.W. (1993). Performances of the Gibbs, hit-and-run, and Metropolis samplers. *Journal of Computational and Graphical Statistics*, **2**, 251-272.

The authors propose a general form of the hit-and-run algorithm, which behaves like a random-direction Gibbs sampler and allows for a complete exploration of a randomly chosen direction. The hit-and-run algorithm is particularly useful when the sample space is sharply constrained.

- Duane, S., Kennedy, A.D., Pendleton, B.J. and Roweth, D. (1987). Hybrid Monte Carlo. *Physics Letters B*, **195**, 216-222.

The authors propose the hybrid Monte Carlo algorithm which combines the basic idea of molecular dynamics and the Metropolis acceptance-rejection rule to produce Monte Carlo samples for a complex distribution.

- Edwards, R.G. and Sokal, A.D. (1988). Generalization of the Fortuin-Kasteleyn-Swendsen-Wang representation and Monte Carlo algorithm. *Physical Review D*, **38**, 2009-2012.

The authors propose the slice sampler which seeks to generate samples which are uniformly distributed in a region under the surface of the target density function. A marginal distribution of the sample is identical to the target distribution.

- Gelfand, A.E. and Smith, A.F.M. (1990). Sampling-based approaches to calculating marginal densities. *Journal of the American Statistical Association*, **85**, 398-409.

The authors demonstrate that the conditional distributions needed in the Gibbs sampler are commonly available in many Bayesian and likelihood computations.

- Geman, S. and Geman, D. (1984). Stochastic relaxation, Gibbs distributions and the Bayesian restoration of Images. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, **6**, 721-741.

The authors propose the Gibbs sampler which turns out to be a special scheme of the Metropolis-Hastings algorithm with the proposal distributions being the conditional distributions derived from the target distribution. In the Gibbs sampler, the components of

the parameter vector (multidimensional) can be updated in a systematic or random order.

- Geyer, C.J. (1991). Markov chain Monte Carlo maximum likelihood. *Computing Science and Statistics: proceedings of the 23rd Symposium on the Interface* (ed. E.M. Keramigas), 156-163, Interface Foundations, Fairfax.

The author proposes the parallel tempering algorithm which falls into the class of multiple-chain MCMC algorithms. The invariant distributions of the multiple Markov chains are constructed by scaling (or tempering) the target distribution along a given temperature ladder. The swapping operation, exchange of samples between neighbouring Markov chains, accelerates the convergences of the Markov chains at low temperature levels.

- Geyer, C.J. and Thompson, E.A. (1995). Annealing Markov chain Monte Carlo with applications to pedigree analysis. *Journal of the American Statistical Association*, **90**, 909-920.

The authors consider practical issues of simulated tempering (Marinari and Parisi, 1992), for example, how to set the temperature ladder and how to estimate the pseudo-normalizing constants for each of the trial distributions constructed by scaling (or tempering) the target distribution along a given temperature ladder. The authors also demonstrate the usefulness of the algorithm through a biomedical example.

- Gilks, W.R., Roberts, G.O. and George, E.I. (1994). Adaptive direction sampling. *Statistician*, **43**, 179-189.

The authors propose adaptive direction sampling algorithms under the framework of multiple-chain MCMC simulations.

- Green, P.J. (1995). Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. *Biometrika*, **82**, 711-732.

The author presents a variable transformation based treatment for the Metropolis-Hastings moves between two different dimensional spaces and names the moves reversible jumps. The reversible jumps have wide applications in Bayesian model selection.

- Grenander, U. and Miller, M.I. (1994). Representations of knowledge in complex systems. *Journal of the Royal Statistical Society B*, **56**, 549-603.

The authors propose the Langevin algorithm which produces Monte Carlo samples by simulating a diffusion process with the target distribution being its stationary distribution. The diffusion process can be discretized and moderated by the Metropolis-Hastings algorithm.

- Hastings, W.K. (1970). Monte Carlo sampling methods using Markov chains and their applications. *Biometrika*, **57**, 97-109.

The author generalizes the Metropolis algorithm to the case that the proposal distribution is asymmetric.

- Hesselbo, B. and Stinchcombe, R.B. (1995). Monte Carlo simulation and global optimization without parameters. *Physics Review Letters*, **74**, 2151-2155.

The authors propose the $1/k$ -ensemble sampling algorithm, which is similar in spirit to the multicanonical algorithm (Berg and Neuhaus, 1991) and seeks to produce samples from a trial distribution under which the configuration entropy variable is approximately uniformly distributed. The trial distribution can be constructed in the same procedure as that used in the multicanonical algorithm.

- Hukushima K. and Nemoto, K. (1996). Exchange Monte Carlo method and application to spin glass simulations. *Journal of the Physical Society of Japan*, **65**, 1604-1608.

The authors propose the exchange Monte Carlo algorithm which is a reinvention of parallel tempering (Geyer, 1991).

- Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P. (1983). Optimization by simulated annealing. *Science*, **220**, 671-680.

The authors propose simulated annealing (SA) as a general-purpose optimization algorithm. SA employs a temperature parameter to control simulation or optimization of the target distribution. As shown by Geman and Geman (1984), if the temperature decreases sufficiently slow (i.e., in the logarithmic rate), SA can reach the global energy minima with probability 1 as the running time goes to infinity.

- Kou, S.C., Zhou, Q. and Wong, W.H. (2005). Equi-energy sampler with applications in statistical inference and statistical mechanics. *Technical Report, Department of Statistics, Harvard University*.

The authors propose the equi-energy sampler which can be viewed as a new implementation of the multicanonical algorithm (Berg and Neuhaus, 1991) in the style of multiple-chain MCMC.

- Liang, F. (2002). Dynamically weighted importance sampling in Monte Carlo computation. *Journal of the American Statistical Association*, **97**, 807-821.

The author proposes the dynamic importance sampling algorithm in which the trial distribution can be self-learned and the importance weight becomes a random variable.

- Liang, F. (2005). Generalized Wang-Landau algorithm for Monte Carlo Computation. *Journal of the American Statistical Association*, in press.

The author generalizes the Wang-Landau algorithm (Wang and Landau, 2001) based on a partition of the sample space. The generalized algorithm is applicable to many statistical problems, such as model selection and sampling of complex distributions. The generalized algorithm has also incorporated some features of $1/k$ -ensemble sampling (Hesselbo and Stinchcombe, 1995) and, hence, it is attractive to optimization.

- Liang, F., Liu, C. and Carroll, R.J. (2005). Stochastic approximation in Monte Carlo computation. *Technical Report, Department of Statistics, Texas A&M University*.

The authors propose the stochastic approximation Monte Carlo algorithm which can be regarded as a stochastic approximation extension of the Wang-Landau algorithm (Wang and Landau, 2001). This work also represents a new development of the stochastic approximation method, extending the applications of stochastic approximation to Monte Carlo computation.

- Liang, F. and Wong, W.H. (2000). Evolutionary Monte Carlo: Applications to C_p model sampling and change point problem. *Sinica Sinica*, **10**, 317-342.

The authors propose the evolutionary Monte Carlo algorithm which incorporates the genetic algorithm into MCMC simulations. The algorithm is useful in variable selection and change point identification.

- Liang, F. and Wong, W.H. (2001). Real Parameter evolutionary Monte Carlo and Bayesian neural network forecasting. *Journal of the American Statistical Association*, **96**, 653-666.

The authors extends the evolutionary Monte Carlo algorithm (Liang and Wong, 2000) to the case that the parameters are real variables. Direction sampling algorithms, such as the snooker algorithm (Gilks, Roberts and George, 1994), are adopted as crossover operators.

- Liu, C. (2003). Alternating subspace-spanning resampling to accelerate Markov chain Monte Carlo simulation. *Journal of the American Statistical Association*, **98**, 110-117.

The author proposes to accelerate MCMC algorithms, such as the data augmentation algorithm (Tanner and Wong, 1987) and the Gibbs sampler (Geman and Geman, 1984), via partial resampling.

- Liu, J.S., Liang, F. and Wong, W.H. (2000). The use of multiple-try method and local optimization in Metropolis sampling. *Journal of the American Statistical Association*, **95**, 121-134.

The authors propose the multiple-try Metropolis-Hastings algorithm which can be viewed as an importance sampling-based Metropolis-Hastings algorithm. This paper provides a general framework for incorporating optimization procedures, such as steepest descent and conjugate gradient, into MCMC simulations.

- Liu, J.S. and Sabatti, C. (2000). Generalized Gibbs sampler and multigrid Monte Carlo for Bayesian computation. *Biometrika*, **87**, 353-369.

The authors propose a general form of the conditional sampling originated in the Gibbs sampler (Geman and Geman, 1984). The generalization is done via groups of transformations.

- Liu, J.S., Wong, W.H. and Kong, A. (1994). Covariance structure of the Gibbs sampler with applications to the comparisons of estimators and augmentation schemes. *Biometrika*, **81**, 27-40.

Based on the theoretical results on the convergence rate of the Gibbs sampler, the authors argue that grouping highly correlated components together (i.e., update them jointly) can improve its efficiency.

- Marinari, E. and Parisi, G. (1992). Simulated tempering: a new Monte Carlo scheme. *Europhysics Letters*, **19**, 451-458.

The authors propose the simulated tempering algorithm in which the sample space is augmented by an auxiliary variable, the index of temperatures. Simulated tempering leads to a random walk along the temperature ladder.

- Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H. and Teller, E. (1953). Equations of state Calculations by fast computing machines. *Journal Chemical Physics*, **21**, 1087-1091.

The authors propose the Metropolis algorithm which forms the cornerstone of the Markov chain-based Monte Carlo methods. At each iteration, the Metropolis algorithm suggests a possible move according to a symmetric proposal distribution and then employs an acceptance-rejection rule to moderate the move such that the detailed-balance condition is satisfied. The detailed-balance condition ensures invariance of the target distribution.

- Neal, R. (2003). Slice sampling (with discussion). *Annals of Statistics*, **31**, 705-767.

The author proposes improvements to the standard slice sampling algorithm based on random walk suppression, which can be done for univariate slice sampling by “over-relaxation” and for multivariate slice sampling by “reflection” from the edges of the slice.

- Propp, J. and Wilson, D. (1996). Exact sampling with coupled Markov chains and applications to statistical mechanics. *Random Structures and Algorithms*, **9**, 223-252.

The authors proposes the coupling from the past(CFTP) algorithm which can be used to draw exact samples from a distribution defined on a finite state space.

- Swendsen, R.H. and Wang, J.S. (1987). Nonuniversal critical dynamics in Monte Carlo simulations. *Physical Review Letters*, **58**, 86-88.

The authors propose a clustering algorithm, which reduces the critical slow down of the Ising and Potts models and has many applications in image analysis. The idea of the algorithm has been extended to a class of auxiliary variable-based MCMC algorithms.

- Tanner, M.A. and Wong, W.H. (1987). The calculation of posterior distributions by data augmentation (with discussion). *Journal of the American Statistical Association*, **82**, 528-540.

The authors propose the data augmentation algorithm which first links the Gibbs sampler structure with statistical missing data problems and the EM algorithm.

- Wang, F. and Landau, D.P. (2001). Efficient, multiple-range random walk algorithm to calculate the density of states. *Physical Review Letters*, **86**, 2050-2053.

The authors propose the Wang-Landau algorithm which can be viewed as an improved implementation of the multicanonical algorithm (Berg and Neuhaus, 1991).

- Wong, W.H. and Liang, F. (1997). Dynamic weighting in Monte Carlo and optimization, *Proceedings of the National Academy of Sciences USA*, **94**, 14220-14224.

The authors propose the dynamic weighting algorithm in which the importance weight becomes a random variable and helps the system to escape from the trap of local energy minima. The authors also introduce the concept of invariance with respect to the importance weights and propose to use it as a general guideline for MCMC simulations in place of the detailed balance condition used by the Metropolis-Hastings algorithm. ▲

SUGGESTIONS

PLEASE, FEEL COMPLETELY FREE TO SEND US SUGGESTIONS THAT MIGHT IMPROVE THE QUALITY OF THE BULLETIN

jac@cimat.mx

BAYESIAN METHODS IN STATISTICAL DISCLOSURE LIMITATION

by Jerome Reiter
jerry@stat.duke.edu

When releasing data to the public, statistical agencies are obligated by law to protect the confidentiality of respondents' identities and sensitive attributes. Stripping unique identifiers—like names, addresses, and government-issued identification codes—from the file may not adequately protect confidentiality, because data snoopers may be able to link records in the released data to records in external databases by matching on common values in the two files. Most agencies therefore alter the original data before disseminating them, for example by coarsening or adding noise. In this article, I review the role Bayesian methods play in the evaluation and development of confidentiality protection strategies.

To select confidentiality protection strategies, agencies seek to maximize the usefulness of the released data for acceptable levels of disclosure risks. Many agencies employ Bayesian techniques to quantify risk and utility, often implicitly and sometimes explicitly. To measure risk, agencies can apply Bayes rule to compute probabilities of identification for the records in the observed file, given the released data and publicly available information about target records. Another approach is to estimate the number of records in the observed dataset that have unique characteristics in the population. Such estimations can be improved by incorporating prior information and borrowing strength across small areas, tasks ideally handled by Bayesian methodology. To measure data utility, agencies often compare *ad hoc* summaries of the released data, such as first and second moments, to corresponding summaries in the original data. Another approach is to determine the amount of overlap in posterior distributions of specific parameters when estimated using the original and the altered data. More broadly, one can frame utility analysis as an exercise in Bayesian decision theory.

Bayesian thinking underpins several approaches for releasing confidential data. For record-level data, one proposal is to release multiply-imputed,

synthetic datasets. These data are simulated from posterior predictive distributions estimated using the original data. Inferences from the synthetic datasets are obtained using methods like those from multiple imputation for missing data, although different rules are used for combining point and variance estimates across the multiple datasets. For tabular data, one proposal is to generate new tables from posterior distributions conditional on certain marginal counts. These are generated using importance sampling and techniques from computational algebra.

There is much opportunity and need for Bayesian statisticians to advance research on data confidentiality. To learn about this area of research, I suggest starting with the sources listed below.

1. Willenborg, L. and de Waal, T. (2000), *Elements of Statistical Disclosure Control*. Springer Verlag: New York.
This is an overview of disclosure limitation techniques used by national statistical agencies.
2. Bill Winkler's bibliography on data confidentiality: <http://www.niss.org/affiliates/totalsurveyerrorworkshop200503/presentations/WinklerConfidRef050211.pdf>.
3. Web sites for the National Institute of Statistical Sciences Digital Government projects (<http://www.niss.org/projects.html>) and the ASA Committee on Privacy and Data Confidentiality (<http://www.amstat.org/comm/cmtepc/index.cfm?fuseaction=main>).
These web sites contain links to a variety of research.
4. UNECE workshop on data confidentiality (<http://www.unece.org/stats/documents/2005.11.confidentiality.htm>).
See the papers by Karr et al., Forster, Poletini and Stander, Ting et al., and Trottni.
5. CHANCE magazine, Summer 2004.
This is a special issue on data confidentiality with introductions to synthetic data, tabular data, and risk/utility tradeoffs.▲

SOFTWARE REVIEW

BAYESIAN CLINICAL TRIAL SOFTWARE FROM MDACC

by John D. Cook
M. D. Anderson Cancer Center
cook@mdanderson.org

Introduction

This note briefly describes some of the software developed by the Department of Biostatistics and Applied Mathematics at M. D. Anderson Cancer Center for Bayesian clinical trial methods. All applications presented here have a Windows graphical user interface and are freely available from the following web site:

<http://biostatistics.mdanderson.org/SoftwareDownload>

CRMSimulator

There have been numerous variations of the CRM (Continual Reassessment Method) for phase I dose-finding based on toxicity. The **CRMSimulator** strips the CRM down to only those features we have seen most commonly used in practice and emphasizes simplicity rather than generality. It is intended as a pedagogical tool, an easy-to-use application for those new to adaptive clinical trial methods. Graphical controls allow the user to visualize the prior probabilities of toxicity and the target toxicity.

EffTox

The **EffTox** application implements the method of Thall and Cook [3] for dose-finding based on efficacy and toxicity outcomes. Rather than searching for a moderately toxic dose, the EffTox method attempts to find a dose maximizing efficacy and minimizing toxicity, using utility trade-offs elicited from physicians. The method is thus useful for phase I/II trials, evaluating safety and efficacy at the same time.

The software allows physicians to visualize their utility contours, aiding the elicitation process. One may enter model hyperparameters directly, but the software can solve for hyperparameters that cause the model to match elicited prior probabilities. EffTox supports trial simulation and conduct.

Multc Lean

The **Multc Lean** is a “lean” version of the **Multc99** software implementing the multiple comparison safety monitoring method of Thall, Simon, and Estey[4]. Multc Lean monitors only two outcomes, efficacy and toxicity, rather than the complex combinations supported by its predecessor. And while Multc99 is a command line application, Multc Lean has a Windows user interface. Multc Lean offers the user one option not available in Multc99, and that is the ability to simulate expected trial duration.

Adaptive Randomization

The **Adaptive Randomization** software provides a unified environment for simulating a wide variety of adaptively randomized trials. Both binary and time-to-event endpoints are supported. See Berry and Eick[1] for some background on adaptive randomization.

Predictive Probabilities

For trials with either binary or time-to-event outcomes, **Predictive Probabilities** computes the predictive probabilities of various events, such as concluding that one arm or the other is superior or stopping a trial due to futility. This software is often used in designing clinical trials and in conducting interim analyses.

Inequality Calculator

Given two random variables X and Y , the **Inequality Calculator** calculates $P(X > Y + \delta)$ and produces graphs of the densities of the two random variables. This sort of random inequality is at the heart of many safety monitoring rules, such as [4] and [5]. The supported distribution families are Beta, Gamma, Inverse Gamma, Log normal, Normal, and Weibull.

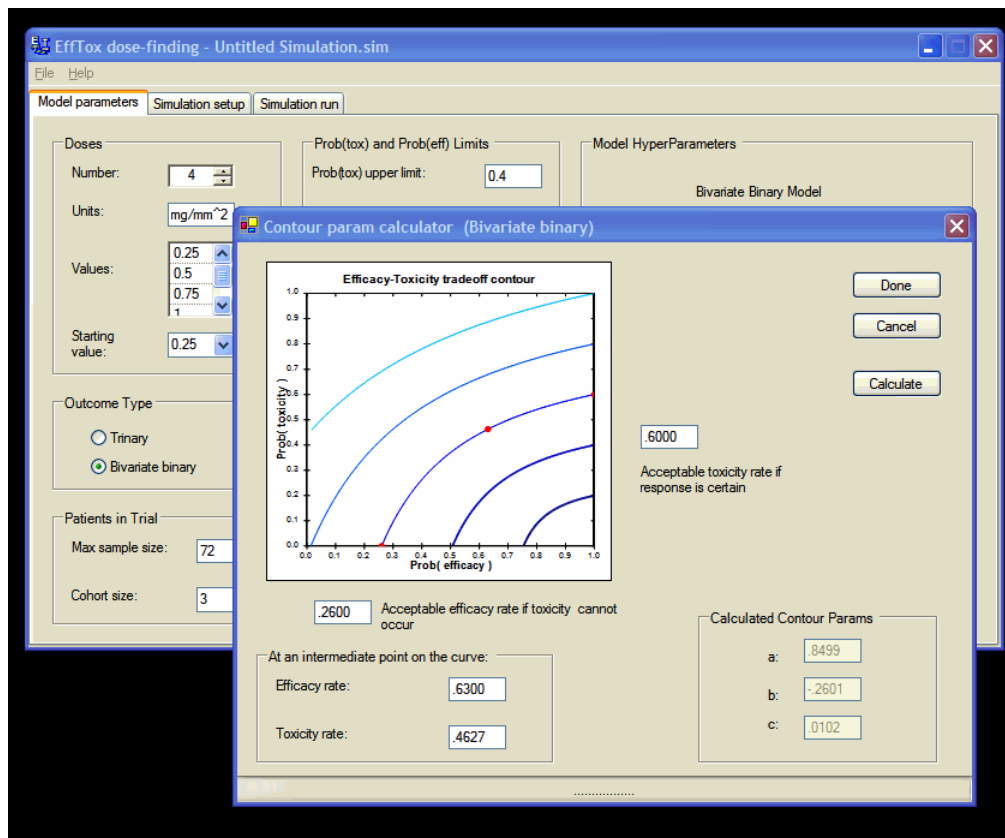
Included in the Inequality Calculator is Parameter Solver, also available separately, for solving for distribution parameters given two quantiles or mean and variance.

References

- [1] Donald A. Berry and G. E. Eick. Adaptive assignment versus balanced randomization in

- clinical trials: a decision analysis. *Statistics in Medicine*, vol 14, 231-246 (1995).
- [2] Donald A. Berry. Bayesian statistics and the ethics of clinical trials. *Statistical Science* Volume 19(1):175-187. (2004)
- [3] Peter F. Thall and John D. Cook. Dose-Finding Based on Efficacy-Toxicity Trade-Offs, *Biometrics* 60, p684-693 (2004).
- [4] Peter Thall, Richard Simon, and Elihu Estey. Bayesian sequential monitoring designs for single-arm clinical trials with multiple outcomes, *Statistics in Medicine*, vol 14, 357-379 (1995).
- [5] Peter F. Thall, Leiko H. Wooten, and Nizar M. Tannir. Monitoring Event Times in Early Phase Clinical Trials: Some Practical Issues, *Clinical Trials*, to appear (2005).▲

Figure 1: Working environment in EffTox application



THE 2006 MITCHELL PRIZE

The Mitchell Prize committee invites nominations for the 2006 Mitchell Prize. The Prize is currently awarded every other year in recognition of an outstanding paper that describes how a Bayesian analysis has solved an important applied problem. The Prize is jointly sponsored by the ASA Section on Bayesian Statistical Science (SBSS), the International Society for Bayesian Analysis (ISBA), and the Mitchell Prize Founders' Committee, and consists for 2006 of an award of \$1000 and a commemorative plaque. The 2006 Prize selection committee members are Tony O'Hagan (chair), Dave Higdon and Marina Vannucci. This information is reproduced from <http://www.bayesian.org/awards/mitchell.html>, where more details may be found.

MY EARLY DAYS AS A BAYESIAN

by Tony OHagan

a.ohagan@sheffield.ac.uk

How I became a Bayesian

I took the BSc Statistics course at University College London from 1966 to 1969. In my second year, Dennis Lindley moved to UCL to take over as Professor from Maurice Bartlett. Until then, the teaching had of course been exclusively frequentist, but Dennis introduced a short lecture course for final year students on Decision Theory. This dealt with Bayesian hypothesis testing and point estimation as decisions, as well as conjugate priors and value of information.

Dennis was a superb lecturer, who conveyed enthusiasm for his subject and challenged our perceptions. I enjoyed his course probably more than any other in my final year. However, I left UCL unconvinced that all the frequentist theory I had been taught could be useless. After all, at least 999 of every thousand statisticians were happy with the standard methods – could they all be wrong?

I left UCL to work for the Central Electricity Generating Board (CEGB), in the small Statistics section that was based in their Computing centre in Bankside, London. (We were right next to Bankside power station, which is now the famous Tate Modern art gallery.) My work involved designing and analysing experiments for the CEGBs scientists in their research laboratories. I was particularly responsible for the work of their nuclear power laboratories at Berkeley, Gloucestershire. My first task was analysing a large factorial experiment with split plots and cyclical factors, and of course I did this using standard classical methods.

However, it was during the two years that I worked for the CEGB that my conversion took place. And it happened because of how the scientists interpreted the results that I gave them. When I presented them with an estimate for some parameter, I could see them mentally comparing it with their expectations, with results from similar experiments, and so on. As a result, they would invariably feel that the true value was more likely to be on one side of my estimate than the other. And when I presented them with a confidence interval they would automatically interpret it as a probability statement about the uncertain parameter (for fixed interval). Because I had received Dennis Lindleys excellent undergraduate course at UCL, I realised that the scientists I was working with were

all natural Bayesians. The 999 frequentist statisticians in every thousand were in fact heavily outnumbered by Bayesian non-statisticians!

I remain convinced to this day that everyone is born a Bayesian, and only loses this state of grace when corrupted by the fallacious teachings of frequentists.

An early proposal for sampling-based inference

One piece of work that I did at the CEGB illustrates how my thinking had shifted firmly to a Bayesian perspective in less than two years. The work at Berkeley at that time was strongly directed towards research for the new advanced gas-cooled reactors (AGRs). Within the reactor core, assemblies of 36 fuel rods had gas passed over them to take the heat generated in the fuel away to the turbines. It was important that the transfer of heat from the stainless-steel casing of the fuel rod to the gas was very efficient, so as to prevent over-heating in the assembly. That first experiment I had analysed was measuring the heat transfer at many points in a fuel rod assembly (actually one for the previous generation of magnox reactors).

The analysis of such experiments yielded a fitted regression model, but the question of interest was, what would be the lowest heat transfer value achieved at any point in the assembly? If this was too low, there was a risk of the fuel casing rupturing, with devastating results. Thinking as a Bayesian, I could see that the experiment ought to provide a posterior distribution for this minimum heat transfer coefficient. I could also see that with weak prior distributions the posterior distribution for the parameters of the fitted regression model would be like the standard frequentist analysis. But the only way I could see of calculating the posterior distribution of interest was by simulating from the posterior distribution of the regression parameters and computing the minimum point from each simulated regression.

This idea was never carried out, partly because of the limited computational power we had then. The CEGB had one of the largest and fastest computers in the UK at the time. It occupied its own air-conditioned room to which only the operators had access, but it had only 384kB of RAM. The PC that I am writing this on has about a thousand times as much main memory and is probably at least a thousand times as fast. Any program I wanted to run had to be submitted on punched cards, and I would

get the output on fan-fold paper a couple of hours later. Writing and debugging a program (even the very simple programs we could run in those days) took weeks when we could only do two or three runs a day.

My method was set out in an internal report that I wrote. For some reason, the report was classified as confidential, and I long ago lost the only copy I had. I doubt very much whether the successors of the CEGB have archives of those old reports, so I suppose it really is lost now. The idea of simulating from the posterior is a commonplace feature of modern Bayesian methodology, in particular as a feature of MCMC, but no doubt there were others using the idea before that. Does anyone know of any other instances as early as 1971?

Return to UCL

I had always intended to do a PhD. Indeed, when I left UCL I already had a grant. At that time, the Science Research Council were running a scheme whereby one could be awarded a grant for a PhD on graduation, but this grant was to be taken up after spending from one to five years in industry or teaching. This was a wonderful idea, and I have always been grateful for the opportunity it gave me to experience the real world before becoming an academic. All other PhD grants then were awarded to university departments to give to the best students who applied to study there (as is basically the case now). Mine was awarded to me personally, and I could take it to any university that would have me – another excellent feature of the scheme. Having been converted to Bayesianism, I naturally took myself back to UCL to study for my PhD under Dennis Lindleys supervision.

I brought with me topics that I wanted to work on, and which had been suggested by my time at the CEGB. One of these was how to formulate optimal experimental design so that the solution did not involve putting points at the limits of the design space. My experience had shown me that this

dependence on an arbitrary definition of the design space was quite unrealistic in practice. I did not solve this until my 1978 paper in JRSSB (which is now remembered for my early use therein of a Gaussian process to model the regression function). Instead, I started working on the simpler optimisation problem of inference about the location of the maximum of a response surface. This led to my first published paper (in *Biometrika* in 1973), but I got stuck on the question of inference about a ratio of parameters and switched to a different topic that Dennis suggested (simultaneous equations models in econometrics). My thesis is therefore a rather undistinguished mixture of ideas. However, it is worth noting a part of it which again anticipated important Bayesian developments.

I needed to integrate an intractable multidimensional posterior density, a familiar problem that has received enormous attention and now is usually tackled by MCMC. I only dared to try two dimensions. My solution was to use two-dimensional (product) Gauss-Hermite quadrature. My bivariate posterior exhibited substantial correlation, and I realised that it would be necessary to rotate the axes to make the quadrature more efficient. I was adopting essentially the same approach as the influential paper of John Naylor and Adrian Smith in *Applied Statistics* in 1982, except that I located the principal axis by searching for the maximum of the density on a small semicircle around the mode.

I claim no special priority for having done this in 1974 – no doubt there were others coming up with similar pragmatic solutions, but it was Naylor and Smith who saw the wide value of this approach, researched it thoroughly and published it. Theirs was the most widely used way of integrating multidimensional posterior densities before MCMC.

I hope that ISBA members will find in these rather self-indulgent memories of mine some echoes of their own experiences. Our roads may have been different, but we have all had to reach the realisation that the Bayesian paradigm is the right one, and we have all faced practical problems in implementing it! ▲

NEWS FROM THE WORLD

by Alexandra M. Schmidt
alex@im.ufrj.br

I would like to encourage those who are organizing any event around the World, to get in touch with me to announce it here.

Events

Statistics for Biological Networks, EURANDOM, Eindhoven, The Netherlands, January, 16th - 18th, 2006.

Detailed information concerning the invited speakers and the logistics may be found at the workshop website:

<http://euridice.tue.nl/frigat/sbn.htm>.

The main topics of the workshop are:

- Gene Regulatory Networks,
- Statistical Analysis of Neuronal Data,
- Graphical Models and Bayesian Networks.

The deadline for applications to participate as a contributed speaker or as a poster presenter is December 1st, 2005. Although contributions are primarily expected to be focussed on the three main topics of the workshop, applications more loosely connected with these main themes will also be considered.

IceBUGS: A Workshop about the development and use of the BUGS programme, Tvärminne Zoological Station, University of Helsinki, Finland, February, 10th - 13th, 2006.

The aim of this workshop is to bring together people working with and on BUGS, providing a platform for BUGS users and developers to discuss and exchange ideas about using BUGS in data analysis. The workshop will consist of both oral and poster session, as well as discussion session where BUGS experts can discuss your problems, and suggest solutions. We are planning for about 30 participants, so the meeting will be fairly small and informal.

The following speakers have already confirmed their attendance: David Spiegelhalter (UK), Nicky Best (UK), Martyn Plummer (France), Brad Carlin (USA) and Andrew Thomas (Finland).

If you are interested in attending and for more details, please email Bob O'Hara (boh@rni.helsinki.fi).

Meeting on High Performance Computing and Statistical Inference, University of Dublin, Trinity College, Ireland, August 23rd - 25th, 2006.

The conference topics are:

- Implementation of statistical analysis with distributed computing;

- Computation for simulation and statistical inference in very large stochastic systems;
- Developments in Markov chain Monte Carlo (MCMC);
- The suitability to parallelization of statistical methods (with a focus on competing approaches to MCMC);
- Challenging statistical applications that test the boundaries of available computing power;
- Grid technologies for statistical analysis;
- Quantum computing and statistical inference

Contributed papers, in the form of an extended abstract of up to 3 pages, are sought for presentation as a talk or a poster.

Deadline for submission of contributed papers is April, 25th, 2006. More details can be found at <http://www.tcd.ie/Statistics/hpcsi/> or contact hpcsi@tcd.ie for more information.

COMPSTAT 2006: 17th Conference of the International Association for Statistical Computing (IASC), Rome, Italy, August, 28th - September 1st, 2006.

IMPORTANT DEADLINES:

January 15, 2006: Deadline for submission of contributed papers for possible publication on Conference Proceedings.

May 2, 2006: Deadline for submission of contributed abstracts (not included in Conference Proceedings)

More details can be found at w3.uniroma1.it/compstat2006. ▲

THE 2006 DEGROOT PRIZE

The DeGroot Prize is awarded to the author or authors of a published book in Statistical Science. The Prize is named for Morris ("Morrie") H DeGroot, and recognizes the impact and importance of his work in Statistics and Decision Theory, and his marked influence on the evolution of the discipline over several decades through his personal scholarship, educational and professional leadership. Award winning books will be textbooks or monographs concerned with fundamental issues of statistical inference, decision theory and/or statistical applications. Nominations for the 2006 award must be received by Friday, 6th January 2006. Only books published during the 5 year period ending December 31, 2004 are eligible for consideration. The winner of the 2006 DeGroot Prize will be announced at the Valencia/ISBA 8 World Meeting on Bayesian Statistics, June, 2006. The webpage <http://www.bayesian.org/awards/DeGrootPrize.html> contains the full list of the committee members and their addresses, nomination procedure and further information about the prize.



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