### THE ISBA NEWSLETTER

Vol. 6 No. 2 June 1999

#### The official newsletter of the International Society for Bayesian Analysis

#### ELECTRONIC ARCHIVE FOR ABSTRACTS

by Robert Wolpert

Editor, ISBA/SBSS Archive
rlw@stat.duke.edu

ISBA, in collaboration with the Section on Bayesian Statistical Sciences of the American Statistical Association (SBSS of the ASA) has founded a searchable Electronic Archive for abstracts of Bayesian papers and conference presentations. The Archive is hosted by the Duke University Institute of Statistics and Decision Sciences (ISDS).

All authors of statistics papers and speakers giving conference presentations with substantial Bayesian content should consider submitting an abstract of the paper or talk to the ISBA/SBSS Bayesian Abstract Archive. Links to e-prints are encouraged. To submit an abstract, or to search existing abstracts by author, title, or keywords, follow the instructions at the abstract's web site,

www.isds.duke.edu/isba-sbss/
The archive is new and some
problems may arise; please
report difficulties or suggestions
to archive@isds.duke.edu.
Conference organizers are also
encouraged to submit Bayesian
session abstracts by e-mail to

the Abstract staff at the address above. Thank you.

#### A WORD FROM THE EDITOR

by Fabrizio Ruggeri

ISBA Newsletter Editor
fabrizio@iami.mi.cnr.it

We are pleased to present you a new issue of the Newsletter. As you will see, relevant ISBA activities, like ISBA 2000 (do not forget the October, 1st deadline!) and the Bayesian archive, are presented along with various articles. As promised, ISBA members (the only recipients of the current issue) are getting a newsletter like a magazine: we will not present theorems and zillions of MCMC runs, but e.g. ways of spending cold, wet Saturday afternoons .... We continue our series of interviews with Steve Brooks, a young, well known researcher. If you want to suggest someone to interview (even if not Bayesian!), please contact the two Associate Editors. We are presenting two stimulating contributions on teaching and applications, due, respectively, to Romano Scozzafava and Mark Glickman. Two Associate Editors have reviewed, respectively, papers on Bayesian methods in epidemiology and software for Model Averaging. A relevant

part of the Newsletter is devoted to present research by recent Ph.D. recipients and candidates: this time we focus on Carnegie Mellon and one of the Ph.D. programmes in Italy. We continue our tour among Bayesian communities worldwide by looking at what happens in Greece, the location of the next ISBA conference. Finally, we have a rich selection of news from the world, partly provided by our Corresponding Editors and ISBA members.

#### Contents

- ➤ Interview with Brooks
  - ◆ Page 2
- Software review
  - ◆ Page 5
- ➤ ISBA 2000
  - ◆ Page 6
- ➤ Bayesian teaching
  - 🕶 Page 7
- Applications
  - ◆ Page 8
- ➤ Bibliography
  - ◆ Page 10
- ➤ Students' corner
  - ◆ Page 12
- ➤ Bayesians in Greece
  - ◆ Page 16
- News from the world
  - ◆ Page 18

#### STEVE BROOKS

by Michael Wiper mwiper@est-econ.uc3m.es

Steve Brooks is one of the foremost workers in MCMC methodology today and is the administrator of the MCMC preprint service (address at the end of the interview). He took his PhD thesis in MCMC with Gareth Roberts at Cambridge and joined Bristol University as a lecturer in 1996. He has recently won the 1999 Royal Statistical Society research prize and will be moving to the University of Surrey as a Senior Lecturer in August 1999. We e-mailed Steve a number of questions about his career and the Bayesian world in general. Here are his responses.

### 1) Why did you decide to become a statistician?

When I came to the end of my degree I was torn between all sorts of careers. In a way this was the default choice, I was always thinking, "I'll just do another course, while I decide what I want to do". I'd always enjoyed Maths and the sense of achievement you got when you solved a difficult problem. I'd also been strongly attracted towards working on something that could really make a difference in the real world. Statistics seemed the obvious area, combining rigorous mathematics with a strong emphasis on applications.

2) Who were/are your
(statistical) heroes? And
why?

I'm not sure I have heroes, but

there certainly quite a few people who have inspired me. One of my biggest influences has been Byron Morgan. He was my MSc supervisor and then I worked with him as a researcher for a year before my PhD. He always manages to ask exactly the right question and we've done (and are continuing to do) some great work together. There are others too, who have had a more hands-off influence on me. People like Persi Diaconis, Bernard Silverman and Adrian Smith. You can't help but admire people like them and hope that one day someone might think of you in the same way.

3) You have worked in Bayesian computation and MCMC from almost the start of your statistical career. What are the most important developments you have seen?

Well I started in this area in 1993, I guess. Back then MCMC was in it's infancy and there's been phenomenal growth over the past 6 years. Methodological advances have to include things like reversible jump MCMC and perfect simulation, which may potentially revolutionise our field. However, I think that these will have less of an impact on the field over time than we might expect. Already we're beginning to see alternative model-jumping algorithms to rival RJMCMC and perfect simulation seems constrained to only a small class of problems at the moment.

Getting away from the methodology, I'd have to say that the BUGS project has had an enormous impact,

particularly in opening up the methodology to practitioners who might not have the computational background to program these things themselves. The introduction of ideas and, in particular, the notation from graphical modelling has also been extremely influential. For example, the expression of a complex statistical model in the form of a DAG seems such a natural thing to do and makes the communication of ideas between statisticians and practitioners so much easier.

4) What do you think will be the next major developments in Bayesian computation?

I can't help thinking that there's some grand sampling scheme out there somewhere and that the algorithms we work with today are just different faces of some more general approach. Of course I've no idea what that is, but I'd love to be the one who sees it first... Also, adaptive MCMC is an area that's never really taken off. The idea of developing algorithms that adapt themselves to the target distribution as the simulation proceeds so as to improve mixing or other desirable properties. This seems like such a natural idea, but there's been very little published work. I would see this as an area with enormous potential.

And in Bayesian statistics more generally?

There's a lot of interest in financial stuff these days. Obviously there's a lot of money in it, but there's some great problems too. State space modelling seems like a big area here, I like the sort of things that Mike West and Neal Shepherd are doing. Spatial modelling is also a big area now that we have the tools to model these processes properly. One major open problem, to me at least, is a more philosophical one and what we should be doing with our models. Should we choose models or average over them? Should we take an M-open or M-closed view? There seems to be no agreement on these sorts of questions and a great deal of work being done to try and develop a coherent interpretation of the Bayesian philosophy to these sorts of questions. Just what does a Bayesian believe about the model? Of course, we now have non-parametric approaches too. Some see these as the way forward, but I'm pretty keen on carefully choosing my model myself. I don't fancy trying to explain a non-parametric approach to any of my Ecologist collaborators for example!

5) How did the MCMC preprint service start? And for the few Bayesians who know nothing about it, what is its purpose?

The idea was first proposed (I think) by Charlie Geyer. It was at one of the Mt Holyoke meetings in 1994. The problem was that the area was developing extremely rapidly and the inevitable delay between submission of papers and their publication often meant that papers were out of date by the time they appeared. The idea of the service was to

provide a central location for papers on MCMC so as to keep the community up-to-date on current developments. Everyone agreed that it was a great idea but nobody had the time to set it up. My PhD supervisor, Gareth Roberts, came back from the meeting and mentioned the idea and I've never really looked back. The basic idea of the service is to maintain a web-based list of preprints or technical reports on MCMC methodology. People can access the site, search the database or check for the latest additions and then download PostScript or PDF files of papers that look interesting. There is also information on relevant conferences and links to code for performing MCMC simulations etc,....

6) Would you like to see more work published on the Web, or do you prefer paper publications?

I must admit I'm a little old-fashioned and prefer to have nicely bound and presented journals rather than whole piles of reprints on my shelves. I really do like the idea of publishing preprints on the Web, though. I think it helps the community grow faster. Of course, you do have to be a little careful; Web-based material is rarely refereed and there has been the odd problem with papers sent to the preprint list, for example.

7) What advice would you give to teachers of Bayesian statistics? How do you make teaching MCMC simple?

I find it's much easier to learn if the students feel involved with a class. I like using long stories and practical experiments to try help the students get to grips with the concepts. At Bristol, I used to teach Bayesian statistics to third year undergraduates, who had never come across the ideas before. So, it was important to try and put the Bayesian ideas across within the frequentist world in which they'd been brought up. One of my favourite ways of doing this is to tell them the following story. "Suppose you're relaxing in your favourite chair early one morning and staring out of the window across your front lawn. Your eye casually falls on a large object in the middle of the lawn. It looks like a large and long pole standing upright with lots of small green bits hanging off of what look like brown arms. As it gently sways in the breeze you entertain two possibilities; either it is a tree or a mailman. Of course you decide it must be a tree because the likelihood of it being a tree, given the description is considerably higher than than that for a mailman. Now suppose you entertain a third possibility; perhaps it's a fake tree. Now, the likelihood tells you nothing and you can't decide between it being a tree or a fake tree. However, a priori you know it's unlikely that someone will have placed a fake tree in your garden and by combining this knowledge with the likelihood, you are able to identify the object as a tree." As I work through this story, I assign letters to the different events and write probability

statements on the board. The idea is to walk them through a simple example with intuitively obvious steps to make the whole idea seem more familiar to them. Most of them realise that they were Bayesians all along, they just didn't know it! MCMC can be taught similarly. One example I use here is to arrange the class in rows. The person on the left-hand end tosses a coin and passes it to the person to their right. This person then tosses two more coins. This person now has three coins and there must be either more Heads or Tails. This person passes to their right one of the coins which shows the side which appears most of the three before them. The next person tosses two coins and looks at those two, together with the one from their left etc,... This simulates a Markov chain, and by starting all of the chains of with Head for example, you can explain the ideas of starting point bias, convergence etc,.... You can then go through the maths and prove that the chain has a stationary distribution putting equal probability on Heads and Tails. Ideas like this help the students to engage with the ideas and to think about them again outside of class. It's also fun!

8) Have you ever had any amusing (Bayes) questions or comments from students in your stats classes?

A few months ago I had a very annoyed student come into my class. She'd been sitting in her car trying to decide whether or not she should buy a parking ticket for 2 pounds or risk a fine of 15 pounds if she were caught without one. The day before, we had gone through a few decision theory problems and she decided to choose the option which minimised her expected loss and didn't buy a ticket. Unfortunately, her prior on the arrival rate of traffic wardens was a bit off and she was fined. She seemed to think the whole thing was my fault!

9) What do you enjoy most about your work?

It's got to be the people. Bayesians in particular seem to be such nice people, just look at the conferences! Of course, I enjoy positive feedback. I've written a couple of review papers in the past few years and it's great to hear people have been reading them, using them for discussion groups etc,... It's a great feeling to know that all the effort it took to put pen to paper was worthwhile and that someone out there appreciates it.

#### And least?

Actually, there's not a lot I don't like about the job. I guess the statistical community, as it becomes more strongly market driven, is much more competitive than it used to be. I find myself watching what I say at conferences a little and trying to not to give my best ideas away before I've had a chance to work on them myself. I've been stung that way a couple of times now, and it saddens me that some people are willing to steal ideas from others. Perhaps it's always been that way, but I always used to have the impression that academics were better than that.

10) What is your favourite statistics book?

I love books, I always have. I probably have around 200 statistics books on my shelves. I guess my favourite book should be the one with the cover most worn, that would probably be Feller "An Introduction to Probability Theory and Applications". However, there are loads of other great books out there. My favourites would have to include Carlin and Louis (Chapman and Hall, 1996); Gelman, Carlin, Stern and Rubin (Chapman and Hall, 1995); Robert (Springer, 1994) and, for teaching, I love Gamerman's book on MCMC.

11) What is your favourite Bayesian statistics joke?

I haven't heard many, but one comment that tickled me recently was when we were on a beach at a recent conference. We had decided to go for a swim and as we were running off, someone shouted "last one in's a frequentist!". It wasn't even a Bayesian conference, but the idea just made me laugh.

As a member of ISBA, what if any changes would you like to see in the Society?

That's hard. I think the idea of an independent conference every four years spaced between the Valencia meeting is a great one and I hope the first one in Crete next year is a great

I guess it might be nice to see ISBA working on both the national and international level. For example, ISBA is often associated with major international conferences, but at the national level, only with the JSM. Perhaps we could think about how we can operate more efficiently on the national level by having a presence at national conferences outside the US, like the annual RSS conferences in the UK for example.

Thanks to Steve for a very interesting interview.
The MCMC preprint service is at http://bris.ac.uk/MCMC/.
The homepage of the Bugs project is
www.mrc-bsu.cam.ac.uk/
bugs/Welcome.html. The books
Steve mentioned are
Carlin, B. and Louis, T. (1996).

Bayes and Empirical Bayes

Methods for Data Analysis, Chapman and Hall. Gelman, A., Carlin, J., Stern, H. & Rubin, D. (1995). Bayesian Data Analysis, Chapman and Hall. Robert, C. (1994) The Bayesian Choice, Springer. Gamerman, D. (1997) Markov Chain Monte Carlo, Chapman and Hall.

#### BAYESIAN MODEL AVERAGING SOFTWARE

by Gabriel Huerta gabriel@bayes.stats.nwu.edu

We review software by

We review software by Raftery, Volinsky and Hoeting.

This software provides S-Plus code that implements Bayesian Model Averaging (BMA) to account for model uncertainty in many statistical models including linear regression, generalized linear models and Cox's proportional hazard models. The S-Plus functions: bic.glm, bic.surv, bicreg and bic.logit written by A. Raftery and C. Volinsky solve the variable selection problem by averaging over the best models according to posterior model probabilities. The function bic.glm (Volinsky) implements the model averaging for a large class of generalized linear models as defined by the S-Plus function *glm*. Choices include: Gaussian, Poisson, Gamma, Inverse Gaussian and Binomial distributions. For survival analysis, the function bic.surv (Volinsky) implements the BMA for Cox's proportional hazard

model. Additionally, the functions bicreg (Raftery) and bic.logit (Raftery) implement model uncertainty for a standard linear regression and a logistic regression respectively. The marginal likelihoods used to compute the posterior probabilities are obtained with the BIC approximation and consequently does not involve a specific prior for the parameters of each model that is averaged. The exploration of the model space follows the principle of Occam's razor or principle of parsimony for scientific explanation. Initially, a leaps and bounds algorithm is performed to produce some candidate or "top" models. When more than 30 independent columns are specified, the S-functions reduce to 30 regressors using a backward elimination procedure. Then, Occam's window is built to only consider those models that have, at least, a posterior probability equal to 1/C of the maximum posterior probability for all models; *C* a value that can be fixed by the user. As an option to the user, the model space may be restricted to eliminate those models that receive less support from the data than some of its

sub-models in terms of posterior probability. In broad terms, the input for the S-Plus functions are vectors, matrices or scalars that define the response variable, the independent variables, the prior probabilities for models, indicators for censored or uncensored data, when appropriate, and specifications for the leaps and bounds and Occam's window steps. The output produces a list of objects that include the posterior probabilities, approximated BIC's, deviances and degrees of freedom for the selected models. Also, it contains the maximum likelihood estimator of each regression coefficient for each selected model, the posterior mean of the coefficients averaged across models and their posterior standard deviations. Furthermore, the function *glib* written by A. Raftery, carries out Bayesian estimation, model comparison and accounts for model uncertainty in generalized linear models, notably logistic regression and

log-linear models. It differs

from the other S-functions in

two aspects mainly. It does not

use the BIC approximation but

carries the Bayesian analysis using a reference set of prior distributions that involve Normal forms. Also, it does not use Occam's window or the bounds and steps algorithm and rather requires that the user specifies all the models to be considered. The output for this function contain lists that have model comparison results, the posterior probabilities for models, posterior means and posterior standard deviations for parameters averaged across models.

Also, the software includes a collection of S-Plus programs that performs Bayesian simultaneous variable selection and outlier identification (SVO) via Markov Chain Monte Carlo model composition (MC³) for a linear regression. The programs are known as BMA.shar and were written by J. Hoeting. The

model allows for mixtures of normal errors with a variance that may be inflated by a scalar factor specified by the user. The priors used for model coefficients and variance are the standard Normal-Gamma conjugate distributions. The basic idea for  $MC^3$  is to explore the model space with Metropolis-Hastings steps where candidate models are proposed within a neighborhood of the current model. The neighborhood is usually defined with either one predictor more or one outlier more or with one predictor less or one outlier less. The inputs of the main function MC3.REG involve the response variable, the matrix of all possible covariables, number of iterations for the MCMC, an initial or candidate model, a list of potential outlying

observations, a parameter indicating the probability that a particular observation is an outlier and the inflation factor for the error variance. As output, the program returns a matrix that has information on the selected models visited at each MCMC, a list of outlying observation for each visited model, the number of times the model was visited and the posterior model probabilities. All these S-functions can be freely used and freely distributed for non-commercial purposes only and downloaded from

www.research.att.com/~volinsky/bma.html

Questions about this software should be addressed to the authors (see their addresses in the above web page.

# Call for session organisers and papers

### **ISBA 2000**

The 6th World Meeting of the International Society for Bayesian Analysis

> Hersonissos, Crete May 28-June 1 2000

We expect to publish many of the theme papers in a special issue of the EUROSTAT journal, "Research in Official Statistics." Full details of the plan and schedule will be announced shortly.

We remind that proposals for sessions or for individual talks must be received by Mike West < mw@stat.duke.edu> (Committee Chair) no later than **October 1**, **1999**. More details are available at the ISBA web site **www.bayesian.org** and in the March issue of the ISBA Newsletter.

#### A CONTRIBUTION

by Romano Scozzafava romscozz@dmmm.uniroma1.it

# Are the Frequentist and Bayes Approaches in Conflict?

I feel that a question such as "Is it desirable to teach both Bayesian and frequentist thinking in an introductory class?" is, in a sense, misleading. In fact (as I stress in my teaching in the Engineering Faculty of "La Sapienza" in Rome) the subjective view of probability is not in contrast with a frequentist (or else a combinatorial, i.e. classical) approach, since the latter can be seen just as particular "methods of evaluation" of a probability. This merged approach easily overcomes barriers created by the usual prevailing opinions, giving up any artful limitation to particular events (such as "repeatable" or "symmetric", not even clearly definable). An event *E* is just any unambiguous proposition that can only assume two "values", 1 or 0 (regarding it as a simple random variable). The lack of information on the actual value of *E* easily paves the way to the introduction, as an "ersatz", of the concept of probability: a value p = P(E) is regarded as an amount to be paid to bet on E, with the proviso of winning a unit amount of money if E occurs and nothing if E does not occur. Then coherence is introduced by the requirement that the choice of *p* would not make the player a sure loser or winner. If *E* is different from  $\Omega$ and ∅ (certain and impossible events), the two possible "gains" are G(E) = -p + 1 (if E occurs),  $G(E^c) = -p$  (if *E* does not occur), and so, since coherence requires that they must not be both negative or both positive, *p* must satisfy -p(1-p) < 0, which is the same as 0 . On the otherhand, when  $E = \Omega$  (or  $E = \emptyset$ ) there is no uncertainty on the outcome of the corresponding bet: the only (certain!) value of the gain is  $G(\Omega) = -p + 1$  or  $G(\emptyset) = -p$  respectively, and so coherence requires that the gain is equal to zero, which gives p = 1 for  $E = \Omega$  and p = 0 for  $E = \emptyset$ . In conclusion, if the subjective probability of *E* (our degree of belief in *E*) is defined as an amount p = P(E) which makes coherent a bet on E, then  $0 \le P(E) \le 1$ . And what about the case of *n* simultaneous bets on the events  $E_1, E_2, ..., E_n$  of a partition of  $\Omega$ ? Let  $P(E_k)$ , k = 1, 2, ..., n, be the amount paid for a coherent bet on  $E_k$ . Clearly, these n bets can be regarded as a single bet on  $\Omega$ with amount  $P(E_1) + P(E_2) + ... + P(E_n)$ , and so coherence requires  $P(E_1) + P(E_2) + ... + P(E_n) = 1.$ So the usual "axioms" of probability are easily obtained

coherence. It is important to stress the fact that, even if the intuitive semantic interpretation of coherence is expressed in terms of (hypothetical!) bets, this circumstance must not hide the fact that its role (that of ruling probability evaluations concerning "many" events) is essentially syntactic. The "combinatorial" and "frequentist" methods of evaluation of probabilities can be easily embedded (the latter through exchangeability) into the general concept of subjective probability. Let me point out that this approach puts in the right perspective all the subjective aspects hidden in the so-called "objectivistic theories". I cannot go here into further details, so I just mention two of my articles (Subjective probability and Bayesian statistics in engineering mathematics education, Int. J. Math. Educ. Sci. Technol., 1987, vol.18, n.5, 685-688; A merged approach to stochastics in Engineering Curricula, European J. Eng. Educ., 1990, vol.15, n.3, 243-250), and - for conditional probability - my short note (Probability assessment and Bayesian inference) in the ISBA Newsletter, Issue n.3, September 1994. I wrote also an elementary text (in Italian, but the title needs not a translation!): Probabilità soggettiva: significato, valutazione, applicazioni, Masson (first edition 1989, fourth edition 1997).

in a very simple way, through

#### RATING COMPETITORS IN ONLINE GAMES

by Mark E. Glickman mg@math.bu.edu

A new Bayesian rating system gradually becomes accepted on popular online game servers.

It's a cold, wet Saturday afternoon, so you're stuck inside. What do you do? Some data analysis? Prove a theorem? No – now is the time to log onto one of many internet game servers and spend the rest of the day competing against others like you in games such as chess, bridge, fantasy baseball, or a role-playing adventure game. The opportunities to play with other humans through internet game servers has increased dramatically over the past several years. Some of the major internet companies like Yahoo, Excite, and Netscape have created their own game areas on which, upon registration, anyone can obtain free access. Typical game servers have anywhere from hundreds to tens of thousands of players online simultaneously. To make competing more enjoyable and interesting, many internet gaming organizations have set up rating systems on their servers. Ratings allow players to assess their skill level, and let them compare their own playing strengths against others. Arguably, the most commonly implemented rating system on internet game servers is due to Arpad Elo, the creator

of a popular system for rating tournament chess players. The system is described in detail in his 1978 monograph (*The Rating* of Chess Players, Past and Present, Arco, 1978). The basic idea of this system is that every player obtains a rating through competition, and this rating changes over time based on the player's results. In typical implementations of Elo's system, ratings range between 0 and 3000, with higher ratings connoting stronger skill. When two players of equal rating compete, the winner gains 16 rating points and the loser loses 16. Defeating a player with a higher rating results in a rating gain of more than 16 points, and defeating an opponent with a lower rating results in a gain of fewer than 16 points. Similarly, players defeated by stronger players will lose fewer than 16 points, and will lose more than 16 points if defeated by a weaker player. Essentially Elo's system is a particular non-linear filter on ratings as a function of game outcomes. The formulas to calculate ratings are so simple that they can easily be carried out using pencil and paper. A rating system for internet game competitors can be viewed as a method for estimating parameters of a time-series model. Every player possesses an unknown strength parameter at a given point in time, but the strength parameters change stochastically over time. The goal of the rating system is to infer these parameters. The Elo system produces point estimates

of the strength parameters after every competition by essentially performing a calculation that approximates a weighted average between the pre-game rating and a game "performance" rating. Thus, to first approximation, the Elo system has a Bayesian flavor: the pre-game rating is treated analogously to a prior, and the information in a game is treated similarly to the likelihood. Despite the simplicity and popularity of Elo's system, there are several obvious problems. One of the main problems is that the system does not recognize the uncertainty in players' ratings. To understand why this is a problem, suppose a player rated 1500 is about to compete against an opponent. If the player's 1500 rating is based on very few game results, so that the 1500 rating is an imprecise estimate of the player's ability, then it would seem reasonable that the game outcome should have a substantial impact on the player's post-game rating. This would be equivalent to assuming a vague prior on the player's strength so that the likelihood mostly determines the posterior. On the other hand, the player's rating of 1500 may be a precise measure (because, for example, the player competes often), in which case the outcome of a single game should not have an appreciable effect on the estimate of the player's strength. Elo's system does not make any distinction between these two situations.

A forthcoming article in *Applied* Statistics (Glickman, Mark E. (1999) "Parameter estimation in large dynamic paired comparison experiments") develops a rating system for competitors that adheres more carefully to a Bayesian framework. Instead of merely providing point estimates of players' skill parameters, the system produces an approximate Gaussian posterior distribution. Thus every player has both a rating (the posterior mean) and an estimate of its uncertainty (the posterior variance). One of the main advantages of this new system is that not only is the posterior uncertainty in a player's strength quantified, but the uncertainty measure is used in the calculations to update players' strength estimates. Prior to a competition, players with large prior variances will potentially undergo dramatic

changes from prior to posterior means. Another feature of the system is that players' strength parameter variances increase over time while not competing. This reflects the notion that there is greater uncertainty in a player's ability as time passes if no evidence of ability is presented.

The development of the rating system in the *Applied Statistics* article demonstrates how a simple rating system can be derived through various approximations as a Bayesian analysis of a state-space model. The article demonstrates how the Elo system can be viewed as a special case of the Bayesian system under the assumption that players' strengths are known with certainty, which, of course, is never the case. The rating system is applied to the analysis of a dataset consisting of all known games between the best chess players of all time,

and to the analysis of recent tennis matches among 1100 professional players competing in the ATP Tour. This new system (now being called the "Glicko" system), is currently used by several internet game servers. The "Free Internet Chess Server," for example, has been using this system for several years. More recently, this Bayesian system has been adopted by commercial organizations such as Case's ladder, a multi-player gaming league with over a million members who can compete in various internet games. It has also been adopted in role-playing adventure games such as Chron X. For readers who are interested in the system's implementation without the theoretical underpinnings, they can be found at the web site http://math.bu.edu/people /mg/ratings.html.

#### **EPIDEMIOLOGY**

by Siva Sivaganesan siva@math.uc.edu

We present an annotated bibliography of Bayesian applications in Epidemiology.

To date Bayesian ideas have had limited impact on the practice of epidemiological research (as distinct from the development of biostatistical methodology where Bayesian methods seem to be more widely used), but this may be changing. For instance, the following paper by Sander Greenland presents a very interesting philosophical discussion promoting the role of subjective probability arguments in epidemiological analysis:

• S. GREENLAND (1998).

Probability Logic and

Probability Induction.

Epidemiology 9(3), pp322-32.

Contact: Sander Greenland,

UCLA School of Public Health, USA.

In this paper the author defines the notion(s) of probability, and argues that probability logic recognizes prior distribution as an integral part of statistical analysis, rather than the current misleading practice, in Epidemiology, of pretending that statistics applied to observational data are objective. After presenting arguments in favor of the subjective prior approach, as opposed to the objective or non-informative prior approach, the author suggests that a hierarchical Bayes or empirical Bayes approaches may fall in between the two, and that these are well

suited to many epidemiological studies.

The significance of the above paper was highlighted by a short editorial by another prominent epidemiologist, Malcolm Maclure, in the same issue of the journal (Epidemiology 1998;9(3):p233), entitled "How to Change Your Mind". This piece describes how the author has been persuaded to Greenland's point of view, and highlights the fact that epidemiology has been dominated by the traditional fear of "subjectivity", presumably inculcated by long exposure to frequentist statistical dogmas. Another recent paper presents a simple discussion of the pragmatic application of Bayesian "uniform-prior" or *non-informative prior* approach:

• P. R. BURTON, L. C. GURRIN AND M. J. CAMPBELL (1998). Clinical significance not statistical significance: a simple Bayesian alternative to p values. Journal of Epidemiology & Community Health 52(5); pp318-23.

Contact: P. R. Burton, TVW Telethon Institute for Child Health Research, West Perth, Australia.

In the above paper the authors state that the frequentist confidence intervals have a Bayesian uniform prior interpretation, and that inference constructed using the corresponding posterior distribution is more informative and more easily understood. They illustrate this by using existing frequentist results from a public health study, and using

them to make posterior probability statements, with respect to uniform prior, that are useful in interpreting these results and help in public policy decision making. They predict that with the arrival of general purpose Bayesian software, such as BUGS, it is probable that Bayesian analysis will become common place. Also, in the book:

- Kenneth J. Rothman and SANDER GREENLAND (1998). Modern Epidemiology, 2nd. Ed parts of various chapters are devoted to the foundation and application of Bayesian methods as applicable to Epidemiology. The authors specifically argue that in non-experimental studies, the so-called objective frequentist methods (such as the significance tests and confidence intervals) lack the objective repeated-sampling properties, and that a rational (if subjective) assessment may be the only thing of interest that one can get out of a statistical analysis of observational epidemiological data. Another article promoting the use of Bayesian methods is:
- R. J. LILFORD AND D. BRAUNHOLTZ (1996). The statistical basis of public policy: a paradigm shift is overdue. British Medical Journal, 313(7057): pp603-7.

Contact: R. J. Lilford, University of Birmingham, UK.

Here, it is argued that the conventional statistical tests and estimates are an improper basis for public policy as they dichotomize results according to whether or not they are

significant, thereby tending to produce an on/off response by decision makers. They state that health issues are much more complex and that only the Bayesian approach can provide the probabilistic basis for appropriate action or inaction in public policy matters relating to environmental health.

Other articles using Bayesian and related methodology include:

• P. JORDAN, D. BRUBACHER, S. TSUGANE, Y. TSUBONO, K. F. GEY AND U. MOSER (1997). Modeling of mortality data from a multi-center study in Japan by means of Poisson regression with error in variables. Int. J. Epidemiology 26(3), pp501-7.

Contact: Paul Jordon, Hoffmann-La Roche Ltd., Basel, Switzerland.

Here, relative risk of stomach cancer associated with plasma lycopene level in age-specific populations was modeled using a Poisson regression model with over dispersion and errors in variables. The authors comment that the Bayesian approach allow the estimation of the relative risk in their study with

small sample sizes and low number of cases.

• J. S. WITTE, S. GREENLAND, R. W. HAILE AND C. L. BIRD (1994). Hierarchical regression analysis applied to a study of multiple dietary exposures and breast cancer. *Epidemiology* 5(6), pp612-21.

Contact: John S. Witte, Case Western Reserve University, USA.

In the above article a hierarchical regression approach is used, where a regression model using a new set of underlying covariates is used in the second stage, to estimate the effects of certain dietary exposures to breast cancer. Here, in what the authors call a semi-Bayes approach, the second stage standard deviation is specified through subjective elicitation and the models in the first stage is fitted first, and the results are used in fitting the second stage model. This approach gives more stable and plausible estimates than the one-stage maximum likelihood logistic regression.

• L. Watier, S. Richardson, D. Hemon (1997). **Accounting** 

for pregnancy dependence in epidemiologic studies of reproductive outcomes.

Epidemiology 8(6), pp629-36. Contact: L. Walter, Institut National de la Sante et de la Recherche Medicale, France.

Contribution of hierarchical mixed models to the analysis of epidemiologic studies of environmental exposure and reproductive outcomes is evaluated. A logistic-normal mixed model is fitted using Bayesian and maximum likelihood approaches to data from four studies investigating the relation between the frequency of spontaneous abortions and paternal or maternal environmental exposures. The fitted models allow for between-woman variation of the propensity for spontaneous abortion, by including a random intercept in the logistic model to adjust for within-woman correlations on pregnancy outcomes. We are helpful to John B. Carlin of University of Melbourne, Australia for his help on some of the references.

#### RECENT RESEARCH

by Sudipto Banerjee sudipto@stat.uconn.edu

### We present some abstracts by Ph.D. students.

Ilaria Di Matteo is a Ph.D candidate under the supervision of Dr. R. Kass in Carnegie Mellon University, Pittsburgh. Ilaria has worked on Bayesian Curve Fitting using Spline functions. We also present abstracts of two papers from CMU. Both of them have been sent by J. R. Lockwood, a graduate student at CMU. The first paper deals with modelling the distribution of arsenic in water treatment systems under a Bayesian Hierarchical set-up. He is co-authored by Professor M. Schervish of the Department of Statistics at CMU, Patrick Gurian, a graduate student in the Department of Engineering and Public Policy, and Professor Mitchell Small of the Department of Engineering and Public Policy and Civil Engineering. His second contribution is a paper in Statistical genetics co-authored by Professor Kathryn Roeder of the Department of Statistics in CMU and Professor Bernie Devlin of the Department of Psychiatry in the University of Pittsburgh. We present an abstract from the dissertation by Herbert Lee of the Department of Statistics at CMU. He completed his Ph.D. in December 1998. He has developed a methodology to perform Bayesian non-parametric regression using neural networks. We finally present the abstracts of three recent Italian Ph.D.

dissertations.

#### Papers at Carnegie Mellon University

#### Ilaria DeMatteo

dimatteo@stat.cmu.edu Bayesian Curve Fitting using Splines

Advisor: Robert Kass

Regression splines represent a very flexible tool to estimate curves, but they heavily rely on the choice of the number of knots ad their location. Several methods have been suggested to search for the optimal knot location. We propose a Bayesian method in which the number of knots and their locations are considered parameters, and their posterior distributions are computed through reversible-jump Markov Chain Monte Carlo. The advantage of our model compared to that of Denison Mallick and Smith (1998 *JRSS B*), is that reduces significantly the Mean Square Error, MSE, of the fitted curves. Also, from a small simulation study, our model seems to produce curves having smaller MSE than the Spatially Adaptive Regression Spline developed by Zhou and Shen (1999 Annals of Statistics). A generalization to hierarchical models has been implemented and is currently being studied. We are also developing spline-based curve-fitting methods for non-Normal data.

#### J. R. Lockwood, Mark J. Schervish, Patrick Gurian and Mitchell Small

jlock@stat.cmu.edu
mark@stat.cmu.edu

gurian+@andrew.cmu.edu ms35+@andrew.cmu.edu

The 1996 amendments to the US Safe Drinking Water Act mandate revision of current maximum contaminant levels (MCLs) for various harmful substances in public drinking water supplies. The determination of a revised MCL for any contaminant must reflect a judicious compromise between the potential benefits of lowered exposure and the feasibility of obtaining such levels. This regulatory impact assessment requires detailed information about both occurrence of the contaminant and the costs and efficiencies of the available treatment technologies. Our work focuses on the first step of this process, using a collection of data sources to model arsenic occurrence in treatment facility source waters as a function of system characteristics such as source water type, location and size. We fit Bayesian hierarchical models to account for the spatial aspects of arsenic occurrence as well as to characterize uncertainty in our estimates. After model selection based on cross-validation predictive densities, we use a national census of treatment systems and their associated covariates to predict the national distribution of raw water arsenic concentrations. We then examine the relationship between proposed MCL and the number of systems requiring treatment augmentation and we identify classes of systems which are most likely to be problematic.

The posterior distribution of the model parameters, obtained via Markov Chain Monte Carlo, allows us to quantify the uncertainty in our predictions.

#### J. R. Lockwood, Kathryn Roeder and Bernie Devlin

jlock@stat.cmu.edu
roeder@stat.cmu.edu
devlinbj@msx.upmc.edu

Many applications in statistical genetics, such as linkage analysis, require accurate estimates of allele frequencies for populations which may have different evolutionary histories. Given allele counts for a collection of loci and populations, we propose a Bayesian hierarchical model which extends existing empirical Bayesian approaches by allowing for explicit inclusion of prior information about both allele frequencies and inter-population divergence. We describe a methodology for obtaining informative prior distributions for model parameters based on previous research. Using simulated data, we present an application of the model and highlight the features of the data which are incorporated with our structure. We also provide references and partial documentation for our publicly-available code for fitting the model.

#### Herbert Lee

herbie@stat.cmu.edu Model Selection and Model Averaging for Neural Networks Advisor: Larry Wasserman

Neural networks are a useful statistical tool for nonparametric regression. In this thesis, I develop a methodology for doing nonparametric regression within the Bayesian framework. I address the problem of model selection and model averaging, including estimation of normalizing constants and searching of the model space in terms of both the optimal number of hidden nodes in the network as well as the best subset of explanatory variables. I demonstrate how to use a noninformative prior for a neural network, which is useful because of the difficulty in interpreting the parameters. I also prove the asymptotic consistency of the posterior for neural networks.

#### 1999 Ph.D's at Università di Trento, Italy

#### Ilenia Epifani

ilenia@iami.mi.cnr.it Some results about Random Bernstein Polynomials and their applications to Bayesian nonparametric inference Advisor: Eugenio Regazzini

In our dissertation we deal with the Bernstein measure recently suggested by Sonia Petrone as prior distribution to determine a Bayesian nonparametric density estimation for observations in the closed interval [0, 1]. The basic idea of Bernstein measure is simple: every probability distribution function (df) *F* on [0, 1] can be approximated with the Bernstein polynomial

$$B(K, F, x) = \mathbf{1}_{(1,\infty)}(x) + \mathbf{1}_{[0,1]}(x) \cdot \sum_{i=0}^{K} F\left(\frac{j}{K}\right) {K \choose j} x^{j} (1-x)^{K-j};$$

when *K* and *F* are random with law O, the distribution of random Bernstein polynomial B (which is a measure probability on the space of all df on [0, 1], is called Bernstein prior of parameter Q. If K is an integer valued random variable with law h, F is a Ferguson-Dirichlet random distribution function (rdf) with law  $d_{\alpha}$  and Q is equal to the product measure, then the law of B(K, F) is called Bernstein-Dirichlet prior of parameters  $h, d_{\alpha}$ . The Bernstein-Dirichlet measure shares the "large" support of the Ferguson-Dirichlet one and selects continuous distributions with probability 1. Our attention is focused on the characterization of the finite-dimensional laws of the Bernstein-Dirichlet measure through the explicit expressions of mixed moments, derived from the moment-generating function, which is established for the first time in our work. Furthermore, we give a recurrence formula for the mixed-moments which can be used for the numerics. Finally, we determine the posterior distribution of random Bernstein-Dirichlet polynomial B: if  $X_1, \ldots, X_n, \ldots$ are conditionally i.i.d. given B(K, F), the posterior distribution of  $B(K,F) \mid X_1,\ldots,X_n$  is a Bernstein measure with parameters  $h_n(k)$ ,  $\pi_{\alpha_k}$  where  $h_n$ denote the conditional distribution of  $K \mid X_1, \ldots, X_n$ and  $\pi_{\alpha_k}$  is a suitable mixture of

Ferguson-Dirichlet measures

which coincides with the posterior distribution of  $B(K, F) \mid K, X_1, \dots, X_n$ . Then we investigate the distribution of some functionals of B(K, F): for the mean functional we give the df and moment-generating function, whereas for the variance functional we obtain only the moments of any order. The first part of the dissertation ends with a suggested prior distribution of Bernstein-Dirichlet kind for observations taking values in  $[0,1]^m$  which extends the one given by Petrone for the [0, 1] case. Besides the finite-dimensional laws and posterior distribution, we give the laws of some remarkable functionals as the means vector and variances and covariances matrix. Moreover a Bayesian nonparametric estimation of a multivariate density is given. In the second part of the dissertation, the results about the random Bernstein-Dirichlet polinomials are utilized to investigate some properties of the Ferguson-Dirichlet rdf. We give the moments of the mean of a Ferguson-Dirichlet rdf with parameter  $\alpha$ ,  $\int g(x)dF_{\alpha}$ , for every measure  $\alpha$ . In particular, if the support of  $\alpha$  is limited, we use as main tool of our investigation the weak convergence of a sequence of random Berstein-Dirichlet polynomials to the Ferguson-Dirichlet rdf. On the other hand, when the support of  $\alpha$  is unlimited, we construct a suitable sequence of uniformly integrable random variables converging in probability to the mean functional of  $F_{\alpha}$ , such that

the moments of those random variable can be easily computed. Hence, we have carried out a similar investigation for the moments of the variance of a Ferguson-Dirichlet rdf on R and for the mixed moments of the means vector and the covariance matrix of a Ferguson-Dirichlet rdf on  $\mathbf{R}^m$ . The tecniques in the proof of the previous results can be applied to the cases in which the statistical analysis leads to consider simultaneously many "typical values" of the unknown df F of the kind  $(\int_{\mathbf{R}} g_1(x)dF_{\alpha}, \ldots, \int_{\mathbf{R}} g_m(x)dF_{\alpha}).$ 

#### Antonio Lijoi

antonio@iami.mi.cnr.it
Approximating priors by finite
mixtures of conjugate distributions
for an exponential family
Advisor: Eugenio Regazzini

If the statistical model belongs to an exponential family, it is well-known in Bayesian statistics that any prior can be approximated, in the Prokhorov metric, by a suitable finite mixture of conjugate priors. However, no rule for concretely constructing such a mixture is provided. Taking this remark as a starting point, in the dissertation an estimate of the error of approximation is initially given for some special cases. Three examples are considered: Poisson, Bernoulli and Normal model. Correspondingly, once a prior p.m. and a positive  $\epsilon$  are fixed, a set of values for the hyperparameters of the conjugate distributions and a minimum number k of summands in the mixture are

found such that the error of approximation does not exceed

An analogous estimate is provided with reference to the posterior distribution. In other words, the above-mentioned models are taken in consideration and values of the hyperparameters and of the number of elements in mixture are given such that the error of approximation for the prior as well as for the posterior does not exceed  $\epsilon$ . Proofs of these results rely upon the fact that mixtures of point masses are dense, in the topology of weak convergence, and upon the application of a Large Deviations estimate to the conjugate distributions. Bounds for the hyperparameters and for the value to be assigned to *k* suggest that the posterior obtained form the finite mixture converges weakly to the posterior corresponding to the approximated prior, but this convergence is not uniform with respect to the observed sample. The final part of the dissertation is devoted to the formulation of a generalization of previous results to any natural exponential family. Unfortunately, in the general case it is not possible to resort to any kind of Large Deviations estimate. Hence, the method applied in special cases cannot be used and explicit bounds for the hyperparameters and for *k* are not available. However, by means of the Laplace's method, rates of convergence of the approximating mixtures to the prior and to the posterior distribution are determined.

#### Claudia Tarantola

claudia@verdea.stats.aueb.gr
Bayesian Model determination for
Discrete Graphical Models
Advisor: Guido Consonni

A graphical model is a family of probability distributions incorporating the conditional independence assumptions represented by a graph. It is constructed by specifying *local dependencies* of each node of the graph in terms of its immediate neighbours. It is then possible to work locally, obtaining better results in terms of statistical inference and computational efficiency.

In this thesis we fix our attention on the case in which all considered variables are discrete, and the graph is undirect. Furthermore, we consider a particular subclass of graphical models, the so called decomposable models. These models present special features that make the learning process easier.

Our objective is to make inference both on the graphical structure, quantitative learning, and on the parameters characterising the considered distributions, qualitative learning. In order to do this, for each given graph, we assign an Hyper Dirichlet distribution (Dawid and Lauritzen 1993) on the matrix of cell probabilities; such a prior distribution is obtained by marginalisation from the prior conditional on the complete graph. This not only ensure

compatibility across models, but also leads to a prior distribution automatically satisfying the hyperconsistency criterion. Finally, we assign a uniform prior on the class of decomposable graphs. One problem related to the analysis of graphical models is that the number of structure under comparison increases more than exponentially with the number of nodes; for high-dimensional contingency tables the set of plausible models is large, and a full comparison of all the posterior probabilities associated to the competing models becomes infeasible. Hence the necessity to construct computational algorithms able to *explore* efficiently the space of all possible models. Various solutions to this problem have been proposed, the one we suggest is based on the application of Markov chain Monte Carlo techniques (MCMC). Related works in the area are the one by Madigan and York (1995), that introduce an MCMC sampler, called Markov chain Monte Carlo composition  $(MC^3)$ , for the analysis of decomposable models and the one by Dellaportas and Foster (1999) who develop a MCMC sampler for model choice in the general class of loglinear models. In this thesis we present two different samplers which are fully based on local computations and are therefore

efficient. The first sampler is a revised version of the  $MC^3$  algorithm by Madigan and York (1995). It differs from the original version mainly because it incorporates a local condition for checking decomposability, see Giudici and Green (1999). Furthermore, we propose an extension which allows for a hierarchical prior on the cell counts.

The second sampler is based on the Reversible Jump by Green (1995). Our methodology parallels that presented in Giudici and Green (1999) for the analysis of decomposable gaussian models. As in the gaussian case, at each step of the algorithm we update not only the graphical structure (as in  $MC^3$ ), but also the associated parameter vector. Essentially, in the gaussian case, pairwise conditional independence is dictated by the absence of a single parameter, whereas in the discrete case this generally corresponds to non linear constraints on the cell probabilities. Furthermore, in the continuous case the parameter space is polynomial in the number of variables whereas in the discrete case it is exponential. This leads to substantial differences in the data structure.

The performance of the two samplers has been tested with reference to the *Women and Mathematics* data set, well known in the graphical model literature.

#### BAYESIANS IN GREECE

# by Petros Dellaportas petros@aueb.gr

"Well, Petros, you are not the first Greek I know who decided to continue his career in Greece. But you should do a lot of travelling if you want to keep up with good research". Those were the words of Adrian Smith back in 1990 when I told him that my next career step would be the Greek national service and a consequent permanent settlement in Greece. He had visited Greece back in 1987 and he knew that there are not that many Greek academics interested in Bayesian Statistics. The other Greek Bayesian Statistician Adrian meant was George Kokolakis. George got his Ph.D. from University College London in 1978 under the supervision of Dennis Lindley. Then George returned to Greece and he has been working at the National Technical University of Athens since then. He has been the first Bayesian in Greek academia, something who himself sometimes regrets: "It is the first time in my life that I discuss research in my native language and it is both nice and strange" he told me when we first met in 1991. George was the first to introduce Bayesian ideas to Greek University students and he was, for many years, the sole Greek Universities representative in the Bayesian conferences. My first position was at the recently established (1989) Department of Statistics

(www.stat-athens.aueb.gr/) of the Athens University of Economics and Business (AUEB). To my surprise, the department undergraduate syllabus contained a course in "Bayesian Statistics". I have been teaching the course since 1993, -the colleague who was teaching the course was extremely pleased to pass it to me: he confessed to me that he did not agree with a single word of what he was teaching. A course in Bayesian statistics was a great chance to promote Bayesian thinking and now the department has some active Bayesian life. First, some postgraduate courses (non-linear models, generalised linear models) have obtained some Bayesian flavor and our MSc graduates can perform quite demanding analyses of data using BUGS. Second, Yiannis Ntzoufras, the first Greek Bayesian Ph.D. student, submitted his thesis on "Aspects of Bayesian Model and Variable Selection Using MCMC" last month. There are 3 other Ph.D. students. Stefanos Giakoumatos, Mihalis Linardakis and Yiannis Vrontos, currently working on Bayesian problems. They are all expected to finish by the end of next year. And finally, there is a plethora of MSc dissertations written by students who adopt a Bayesian perspective in their analysis. As a result of all this, there are now some colleagues (Dimitris Karlis, Harry Pavlopoulos, Evdokia Xekalaki) who have adopted a Bayesian viewpoint in some of their research activities. Last but not least, Dimitris Politis who is currently

based at University of California, San Diego, visits our department very often and has been collaborating with our research group adopting Bayesian approaches. Although in AUEB the Bayesian group seems to be vivid, there is little happening outside its doors. An interesting exception is Maria Kateri and Takis Papaioannou from the department of mathematics of University of Ioannina who have been working on symmetry and asymetry models for contingency tables from a classical perspective. After publishing a series of papers using classical methodologies, they have recently started exploring these problems adopting a Bayesian viewpoint. Another Bayesian who has recently returned to Athens is Thanasis Katsis, who received his PhD on Baysian Optimal **Experiments for Discrete** Distributions at George Washington University under the supervision of Blaza Toman. He is currently doing his national service. However, we hope that our group will grow. Take for example the list of Bayesians below (you can find this list at www.stat-athens.aueb.gr/~jbn/ grstats\_Bayes.htm). They are not in Greece, but they are Greek. I hope that some of them, if not all, will be in Greek universities some day. Then Adrian might change his wordings to the young Greeks who decide to come back to something like "the research group in Greece is really good, and the sun is shining: I cannot see why you should stay in UK!"

# ➤ Greek Bayesians outside Greece

- Aslanidou Vlachos Helen, Msc graduate (Univ. of Connecticut), Epidemiology Data Center, Univ.of Pittsburgh,
- ruddles.stat.uconn.edu/~helen/.
- Fouskakis Dimitris, Ph.D. Student, School of Mathematical Sciences, University of Bath, UK, www.bath.ac.uk/~mapdf/.
- Frangakis Constantin, Graduate Student, Dep. of Statistics, Harvard University, frangaki@stat.harvard.edu.
- Gatsonis Costantine, Associate Professor, Center for Statistical Sciences, Brown University, alexander.stat.brown.edu/ hpages/gatsonis.html.

- Kornak John, PhD. Student, School of Mathematical Sciences, University of Nottingham,
- www.maths.nott.ac.uk/people/jk.html.
- Melas Dina, PhD Student, Statistics Department, Trinity College, Dublin (Ireland), melasd@tcd.ie.
- Papandonatos George, Center for Statistical Sciences, Brown University,
- gdp@stat.brown.edu.
- Papathomas Michalis, University of Nottingham, PhD Student,
- mpa@maths.nott.ac.uk.
- Skouras Kostas, Lecturer, Dept. of Statistical Science, University College London,

- www.ucl.ac.uk/ ~ucakks1/home.html.
- Spiropoulos Takis, University of Hertfordshire,
- $\verb|t.spiropoulos@herts.ac.uk|.$
- Streftaris Giorgos, PhD
- Student, gst@maths.ed.ac.uk.

   Vlachos Pantelis Visiting
- Vlachos Pantelis, Visiting Research Scientist, Department of Statistics, Carnegie Mellon University,
- www.stat.cmu.edu/~vlachos/.
- Vounatsou Penelope, Post-doc, Dept. of Public Health and Epidemiology, University of Basel www.wb.unibas.ch/sti/ personel/VOUNATSP.htm.
- Yiannoutsos Constantin, Research Associate, Dep. of Biostatistics, Harvard University, costas@hsph.harvard.edu.

# NEWS FROM THE WORLD

by Antonio Pievatolo marco@iami.mi.cnr.it

#### ➤ Events

Second Mexico Workshop on Bayesian Statistics. August 25-27, 1999. Mexico City. The workshop is sponsored by the Mexican Statistical Association. The programme's central activity will be the short course "Bayesian Biostatistics", by Andrew Gelman (Columbia University, USA). Contributed papers will be presented in a plenary poster session; a title and an abstract should be sent by the end of July.

INFO: tameb@sigma.iimas.unam.mx

#### ICES Annual Science

**Conference**. September 29 to October 2, 1999. Folkets Hus, Stockholm, Sweden, One of the theme sessions of the 1999 ICES (International Council for the Exploration of the Sea) Annual Science Conference is on "Bayesian Approach to Fisheries Analysis". The Bayesian methods can provide a powerful basis for quantifying the uncertainty in stock assessments and, when coupled with decision analysis, provide a natural means of communicating this uncertainty to fishery managers, e.g., the short and long-term consequences of candidate management actions. Contributions illustrating the state-of-the-art application of methods for stock assessment and managment and

summarising the pros and cons of the Bayesian approach will be presented. Registration must be made by August 31.

INFO: http://www.ices.dkorcontact Ms M. Azevedo (mazevedo@ipimar.pt)

Foundational Issues and Statistical Practice. October 14-16, 1999. Bibbiena (Arezzo), Italy. This workshop is co-sponsored by the Italian Statistical Society (SIS), the Italian Institute of Official Statistics (ISTAT) and the Bank of Italy. The scientific programme features 8 invited lectures. The focus of the workshop is on how the conclusions of an analysis can depend on which inferential paradigm has been adopted, a critical issue in areas such as sampling theory and statistics in medicine.

INFO: http://pow2.sta.uniroma1.deadline for submission of it/tardella/workshop contributed papers and for

Conference on Bayesian Applications and Methods in Marketing. November 18-20, 1999. Fisher College of Business, Ohio State University, Columbus, USA. Bayesian methods offer a means of more fully understanding issues that are central to marketing by allowing researchers to build integrated models of behavior that can be estimated with limited amounts of data. The conference will bring together leading practitioners and scholars in marketing who use Bayesian statistical methods. The intent of the meeting is fourfold: to provide training to students, practitioners, and academic researchers on both

basic and new Bayesian techniques; to discuss current problems faced by practitioners and data that are available for solving these problems; to discuss new marketing methods and models; to expose researchers in marketing to new advances in Bayesian methods. The conference is being sponsored by a number of different firms who offer hierarchical Bayes software and consulting services to their clients.

INFO: http://www.cob.ohio-state.
edu/Bayes

### Fifth Brazilian Meeting on Bayesian Statistics.

December 9-11, 1999. State University of Campinas (UNICAMP), SP, Brazil. The following topics will be explored: mixture models, MCMC methods, stochastic processes and time series. The deadline for submission of contributed papers and for two plenary poster sessions is September 20, 1999.

INFO: mail to Jorge Alberto Achcar (Jorge@icmc.sc.usp.br)

#### ➤ Internet Resources

Software reviews. A lot of free and commercial software for teaching and research is available these days and many packages implement Bayesian methods. The software reviews that appeared in *Maths&Stats* (a quarterly newsletter published jointly by the CTI centres in Birmingham and in Glasgow) are archived at the CTI Statistics web site.

URL: http://www.stats.gla.ac.uk/cti/

A web site for statistical **computation**. VassarStats is a JavaScript-based site for statistical computation located at Vassar College, Poughkeepsie, New York, USA. Basic frequentist statistical methods have been implemented, but a Bayes' Theorem calculator is also present. Most methods are accompanied by a clear description of the background or by relevant references. This resource is likely to be useful to students or to anyone who wants to review his or her ideas with the help of numerical examples.

URL: http://faculty.vassar.edu Objective Bayesian Methodol-/~lowry/VassarStats.html ogy. June 10-13, 1999. València,

#### ➤ Miscellanea

#### Indian Chapter of the ISBA.

The Indian Chapter of the ISBA publishes a regular newsletter. If you are interested you can contact Dr. S.K. Upadhyay (sku@banaras.ernet.in).

#### Imprecise probability models.

The Journal of Statistical Planning and Inference is to publish a special issue on the topic of imprecise probability models and their applications. The issue will include some of the papers that were presented at the First International Symposium on Imprecise Probabilities and Their Applications (ISIPTA '99), held in Ghent, Belgium, from June 29 to July 2, 1999. The Journal will also consider additional submissions made before September 22 on the following topics: statistical applications of possibility theory, evidence theory, credal sets, or related models; statistical inference based on prior ignorance; studies of the foundations of statistics using imprecise probability models; robust Bayesian methods; frequentist studies of robustness using Choquet capacities or interval-valued probabilities; and innovative statistical methods using imprecise probabilities. People interested in submitting a paper should contact Peter Walley (walley@usp.br) preferably before June 24.

International Workshop on Objective Bayesian Methodology. June 10-13, 1999. València, Spain. There will not be published proceedings, but authors were asked to place their papers on their web sites. Pointers to these will appear on the workshop web site http://www.uv.es/~bernardo/workshop.html, and some of them are already available.

Workshop on Expert Judgement, a review (by Roger M. Cooke). June 21-24, 1999. Alphen-on-the-Rhine, Holland. On June 21-24 the Technical University Delft (TUD) together with the Forschungszentrum Karlsruhe (FZK), the National Radiological Protection Board (NRPB) and Institut de Protection en de Sûreté Nucléaire (IPSN) held a workshop on expert judgement and accident consequence uncertainty analysis for nuclear power plants. The workshop reported on research contracted by the European Commission,

and the US Nuclear Regulatory Commission, consisting of a stuctured expert judgement assessment of uncertainties on modelling parameters for US and European accident consequence models, and a calculation of uncertainties over model endpoints. Participants from 22 countries, including Japan, Australia and the US, attended the workshop. The first two days were devoted to expert judgement methods. Speakers from the US and European teams focused on methods for selecting and training experts, performance measures, performance based weighting, dependence modelling, and probabilistic inversion. The last two days consisted of feeding back results from the expert judgement study to the experts themselves, and discussing overall results of the uncertainty analysis. As a general conclusion, the method of structured expert judgment leads to Bayesian confidence bands which are significantly wider than the spreads of published "best guesses". Eight expert judgement panels were conducted, and the results together with expert rationales are published as EUR and NUREG reports. Soon to appear as EUR reports are uncertainty results for the European accident consequence models, a procedures guide for structured expert judgement, and a report on methodology, including performance weighting, dependence modelling and probabilistic inversion. Information on these publications is available from Louis Goossens (louis.goossens@wtm.tudelft.nl).

### ISBA OFFICERS

#### **Executive Committee**

#### **Board Members**

President: John Geweke
Past-President: Susie Bayarri
President-Elect: Philip Dawid
Treasurer: Valen Johnson

Executive Secretary: Michael Evans

Mark Berliner, Enrique de Alba, Petros Dellaportas, Alan Gelfand, Ed George, Jayanta Ghosh, Malay Ghosh, Jay Kadane, Rob Kass, Daniel Peña, Luis Pericchi, Sylvia Richardson

Web page: http://www.bayesian.org/

### EDITORIAL BOARD

Editor

Fabrizio Ruggeri <fabrizio@iami.mi.cnr.it>

#### **Associate Editors**

### **Corresponding Editors**

Bayesian Teaching
Jim Albert <albert@math.bgsu.edu>

Students' Corner
Sudipto Banerjee <sudipto@stat.uconn.edu>

Applications

Sujit Ghosh <sghosh@stat.ncsu.edu>

Software Review

Gabriel Huerta <gabriel@bayes.stats.nwu.edu>

News from the World

Antonio Pievatolo <marco@iami.mi.cnr.it>

Interviews

David Rios Insua <d.rios@escet.urjc.es>
Michael Wiper <mwiper@est-econ.uc3m.es>

Annotated Bibliography

Siva Sivaganesan <siva@math.uc.edu>

Carmen Armero < carmen.armero@uv.es>

Marilena Barbieri <marilena@pow2.sta.uniroma1.it>

Christopher Carter <imchrisc@ust.hk>

Roger M. Cooke < r.m. cooke@twi.tudelft.nl>

Petros Dellaportas <petros@aueb.gr>

Eduardo Gutierrez Peña <eduardo@sigma.iimas.unam.mx>

Robert Kohn <robertk@agsm.unsw.edu.au>

Jack C. Lee < jclee@stat.nctu.edu.tw>

Leo Knorr-Held < leo@stat.uni-muenchen.de>

Udi Makov <makov@rstat.haifa.ac.il>

Marek Męczarski <mecz@sgh.waw.pl>

Renate Meyer <meyer@stat.auckland.ac.nz>

Suleyman Ozekici <ozekici@boun.edu.tr>
Wolfgang Polasek <wolfgang@iso.iso.unibas.ch>

Raquel Prado <raquel@cesma.usb.ve>

Josemar Rodrigues < josemar@icmc.sc.usp.br>

Alfredo Russo (arusso@unq.edu.ar>

Daniel Thorburn <daniel.thorburn@stat.su.se>

Antonia Amaral Turkman <antonia.turkman@cc.fc.ul.pt>

Brani Vidakovic <brani@stat.duke.edu>

Hajime Wago <wago@ism.ac.jp>

Simon Wilson <swilson@stats.tcd.ie>

Lara Wolfson <1 jwolfson@byu.edu>

Karen Young <mas1ky@ee.surrey.ac.uk>

Mailing address: ISBA NEWSLETTER - CNR IAMI - Via Ampère 56 - 20131 Milano (Italy)E-mail: isba@iami.mi.cnr.itPhone: +39 0270643206Fax: +39 0270643212