THE ISBA NEWSLETTER

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BAYESIAN STATISTICS A VICTIM OF ITS OWN SUCCESS?

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I wonder how many Bayesians – especially those with the statistical educational background of most members of ISBA – appreciate just how widespread and successful our creed has become? Out there in the real world, increasing numbers of people are researching and using Bayesian ideas and methods in a tremendous variety of imaginative ways, often unaware of the controversy surrounding what to them is the only conceivable approach to their problems. I first realised that not only statisticians did Bayesian statistics when, as a newly appointed Lecturer at University College London, I went on an informal excursion to Bayes' tomb, shortly after Dennis Lindley had had it cleaned and restored. Having some trouble locating the right spot, we found the custodian of the graveyard and asked his help. His eyes lit up in recognition. "Ah!" he said, "that'd be the fellow whose work made the moon landing possible, wouldn't it?" It turned out that he had recently been asked to show the tomb to a party of American control engineers, who, while visiting London, had come to pay their respects to the nonconformist minister who had "introduced the Kalman filter". Some years later I paid a brief visit to Lennart Ljung's Automatic Control group in Linkjöping, Sweden, and was amazed to discover just how active and impressive a hotbed of Bayesian research it was. But unfortunately I was unable to get anybody there to come to the upcoming Valencia Bayesian Statistics meeting — even that couldn't compete with their own professional meeting in Hawaii.

We are all aware of the increasing popularity of Bayesian methods for data-analysis in many areas of Science. But there is also much important work being done at a more fundamental level by those who might not consider themselves Bayesians. At my own College, we are very fortunate to have a new unit on "Computational Neuroscience", headed by Geoff Hinton, a pioneer in neural networks, whose current research framework can only be described as Bayesian Expert Systems. There is also a tremendous interest in this area among Computer Scientists, who regard it as part of "Machine Learning", and are making exciting theoretical and computational advances, as well as getting these implemented in "Microsoftware". In 1998 I attended an "Uncertainty in Artificial Intelligence" meeting shortly after Valencia 6, and it was striking how much more work relevant to my own Probabilistic Expert System interests was presented at UAI.

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More recently I attended an excellent public lecture by Chris Bishop, entitled "Adaptive Computation: Current Challenges and Future Opportunities". And what does "Adaptive Computation" turn out to be? Why, nothing but good old Bayesian learning.

We should be pleased that Bayes has become so popular, but there are also dangers, not least that of fragmentation of Bayesian Statistics into non-communicating specialist disciplines. We have already seen similar processes at work in Classical Statistics, with much innovative applied work being described as "Thingometrics", rather than Statistics. We must struggle against this tendency – a vital task, in which ISBA has a major role to play. Fortunately, the non-statistical Bayesians are becoming much more aware of the statistical foundation on which they are building. When I asked Hinton if, during his time in the Computer Science Department at Carnegie Mellon University, he had come across my friends in the Statistics Department, he admitted, somewhat shamefacedly, that "At that time I didn't know that what I was doing was Statistics." That is definitely not the case now. The problem is, rather, that the "statistical Bayesians" may not be keeping up with what the others are doing. We need to make a major effort to educate ourselves, to reach out to those from other backgrounds, and to make ISBA a natural home and meeting-place for all those interested in the Bayesian approach, whatever their origins.

A WORD FROM THE EDITOR

by Fabrizio Ruggeri
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The issue hosts contributions by Phil Dawid, the new ISBA President, and Maria De Iorio, the new Associate Editor in charge of the Student's Corner: welcome to both of them!

In an effort to improve fast delivery of the Newsletter (and reduce costs!), we are offering ISBA members the possibility of receiving the issues by e-mail: see page 23 for details.

ISBA2000 is approaching very quickly: you will find an update at page 7. Many members of the Editorial Board will be in Crete: we are looking forward to discussing with you about the Newsletter. See you there!

ISBA 2000

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

Hersonissos, Crete

May 28-June 1 2000

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SUSIE BAYARRI

by Mike Wiper
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Susie Bayarri is a Professor in the University of Valencia, Spain. She has worked with many of the "famous names" of Bayesian statistics and has produced a large number of articles on a wide variety of themes. She is an ex president of ISBA. We e–mailed Susie Bayarri various questions about her career and the Bayesian world. Here are her responses.

`1. When and why did you first get interested in Bayesian Statistics?`

I would not put it in these terms. My first statistical course ever was taught by Jose-Miguel Bernardo (as well as the second, and the third, and ...) so I had no options whatsoever: I was born Bayesian from scratch! We all knew that we were learning the "right" stuff: we had no idea what the "wrong" stuff was about, but we did know that, whatever it was, it was *very* bad and *very* incoherent. So, I am one of the very few Bayesians who have never been "converted" to Bayesianism! I guess that, in my case, a better question could have been: Were you ever tempted by frequentism and how did you resist the temptation? or perhaps, How did you learn about "non-Bayesianism"?

`2. Who are the people who have influenced you most in your career? (Why and what have you learnt from them?)`

My first influence was, as I said, Jose-Miguel Bernardo. He introduced us to Bayesianism and brought many famous Bayesians to Valencia for talks, seminars, workshops, even before the Valencia meetings started. I enjoyed that first course a lot, and I might have not taken statistics if I have had a different kind of course. He was always supportive and enthusiastic, and guided us in the very first, very influential, steps of our training. He certainly was a leader to all of us and we would have followed him anywhere (even into frequentism!) I like to think about myself that I would have eventually met, and been converted to, Bayesianism, but Jose-Miguel certainly saved us a whole lot of wasted time!

In recent years, a crucial influence for me has been Jim Berger (hey, I am not very original in this, am I?) The most obvious influence comes from his seminal contributions to Bayesian statistics: indeed, my copy of his book is nearly destroyed by use, and a big chunk of what I have done in recent years is directly based or heavily influenced by his work, specially in robust Bayes, model selection and model criticism, but also in less "obvious" areas such as modeling or Bayesian computation. Perhaps more importantly, he has profoundly changed my perception of Statistics (Bayesian and non Bayesian), and the way I used to think about things. He is one of the very few "true" scientists that I know, in that his main motivation is understanding things, instead of implementing his own approach no matter what. Alas, I seem not to have learnt any of his formidable efficiency in dealing with massive amounts of work!

The person who has influenced me the most is Morrie DeGroot, in the sense that there is a "before" Morrie and an "after" Morrie in my professional life. I still remember those days as fascinating (I am talking of 1985-1989; I first went to Carnegie Mellon in 1985, with a postdoctoral Fullbright scholarship to work with Morrie). I learnt everything from him: Not only the technical stuff (for instance, I wasn't aware of the role of conditioning on Bayesian statistics, nor had really thought about the Bayesian versus frequentist implementations. I also learnt lots about modeling, foundations and Decision Theory, specially sequential decision theory), but also many other aspects of the profession. I learnt from him how to write technical papers (He would pass along some tips from Savage, so I guess I learnt from him too). He also taught me how to give talks and address discussants, how to deal with referees and make referee reports myself. His insights were amazing, and he always had these incisive "little questions" that went straight to the heart of the problems. He fascinated me ... he was my hero! I also learnt that academics means "work all the time" (we, of course, worked on Sundays, but also on Christmas eves, New Year days, till the last second before boarding my plane ... all the time, everywhere).

My publications jumped dramatically, and my life changed: now I am stuck with working all the time!. He was also a wonderful human being. His insatiable curiosity was not limited to statistics: he wanted to learn about everything and had an unbelievably vast culture, from arts to music (he was a real expert in jazz), from literature to theater, ... you name it. He was extremely nice to people and had the finest sense of humor. He was also quite involved in the defense of human rights. He was simply an amazing person and a great scientist.

3. You have worked in many seemingly very different areas of Bayesian statistics; queues, opinion pools, p values, experimental design etc. Maybe you could tell us why you got interested in some of these.

Ah! yes, you got that right: I keep changing from subject to subject, and there is not any deep reasons for it. The truth is that I like very many subjects and I am intrigued by all sort of problems. Most inefficiently, I have started many and continued just few of them (I even wasted one and a half years dramatically changing subjects in my Ph.d. thesis, from Bayesian games to goodness of fit!). Sometimes it just happens that I continue one of them for a longer time, and I get to publish something about it.

I remember how I got interested in some subjects, yes. My interest in conditioning and the likelihood function derives from Morrie's course out of Jim and Robert's Likelihood Principle book. All the work on selection models and the comparison of experiments was also originated by one of Morrie's little remarks ("I wonder whether we are better off with a random sample from the whole population or with one that has been taken from a carefully selected set"). A similar thing happened with our work in expert reporting and pooling: Morrie wondered whether it was to the advantage of the experts to "lie" when reporting their predictions to be pulled by a "boss". This further derived into considering how the experts regarded each other.

My work in queues was entirely driven by the previous work of my coauthor and friend Carmen Armero; the subject was lots of fun and she eventually shared it with me. What else? I started work on finite populations after a consulting project in which I realized how little I knew about it. Bayesian robustness is natural to all Bayesians, is it not? I'm of the "old" school in that I like to have a prior to criticize and to wonder about its implications, so, of course, one is quickly led into robustness considerations. My curiosity took definite form in terms of publications when I began working with Jim Berger. Of course, one is then led to wondering about robustness with respect to the likelihood function, and we explored that a bit too.

I was interested in pooling ever since the work in selection models. We explored a bit the effect of selection in scientific reporting and had many interesting conversations with Ingram Olkin, and hence my first contacts with meta-analyses which later spurred related design problems. The work on p-values never really started this way. Jim and I got interested in model checking, but did not like the usual Bayesian p-values approach. We actually were trying to move *away* from p-values! I find it quite funny that we ended up with such wonderful p-values!

4. Jim Berger who was interviewed last time and others (including yourself as you say above) have worked on methods which in some sense attempt to unify classical and Bayesian methods. What is your view of these techniques? Is a unified statistical world getting closer?

I believe that what is getting closer is a pragmatic view of statistics together with a deeper understanding of statistical tools. Some years ago, all was "black and white" and "bad and good"; today, and I hope even more into the future, we get to "colours" and to much more liberal attitudes. We explore many kind of "good" behaviors (as long as they work), and tolerate and even find use of tools that might be obviously bad in some applications. I must admit that I have never purposefully tried to "unify" Bayesianism and frequentism, but I have indeed been interested about frequentist tools and properties, and about their important role in Bayesian

statistics. Maybe in the future only Bayesian formulated solutions that have good frequentist properties will be in use for wide-spread, "automatic" practice. I like to believe that all sensible frequentist procedures will have a Bayesian interpretation of some sort, so that they will be easier to understand and to correctly apply. (I also like to think that all the others will disappear!).

`5. In terms of teaching, do you have any tips for making Bayesian methods interesting for students, especially those who have gone through their university careers seeing only classical ideas until their final year course? I often find they find the philosophy appealing and the maths unappealing.`

You must be lucky and have very mathematically sophisticated students! I have been teaching math students for a number of years now, and I only find them relieved that the maths are not too ugly! A bit more seriously, I think that the students are quite motivated by Bayesian methods. I, however, because of lack of time, do not emphasize much the purely subjective approach and after the first few classes I make the strongest emphasis in the ease by which Bayesian methods solve problems that were difficult before, without even the need of painfully quantifying subjective judgments! An obvious example is that of inference about a proportion or, even better, the comparison of proportions (as well as the very classical ones of prediction, restrictions on the parameter space, etc.) I teach the "objective Bayes" only as a very convenient (and very lazy!) approach to the real McCoy, but they have no objections to buying it. I also make quite a lot of emphasis in the desirable frequentist properties. I have no options but to choose a "light" version of the asymptotic behavior of Bayesian procedures, and can only touch very lightly robustness issues, mainly when talking about hypothesis testing. These could be, of course, tailored to students demanding more maths. But if this is your "problem", then just take a decision theoretic point of view: In the past, I used to have more mathematically sophisticated students, and they would like all decision optimality properties, as well as invariance and complete classes and such. All of this seems so very old fashioned nowadays, however!

I guess that mathematical students could end up in MCMC theoretical stuff. As I said, I have never found a lack of mathematics to be a problem with my students! My main problem is that in the real world they'll use SPSS or SAS, so I try to give them the Bayesian interpretation to, say, ANOVA F tests, and show them how they can do MUCH more than that.

`6. Maybe you could tell us a little about the Bayesian scene in Spain?`

I wish I knew more! I am ashamed to admit that, even though I follow what a group of Bayesians do, I am not aware of very many Bayesians developments that occur outside my very restrictive circle. However, I have the impression that Bayesianism is healthy and growing. In the academic arena, many scientists who would have called themselves anti-Bayesians some few years ago do use some kind of Bayesian analyses now (I don't think they get as far as calling themselves Bayesians, so, according to Jim's definition, I guess that they are not, after all, Bayesians!). However, there is barely any teaching in Bayesian methods. Even Departments with heavy component of Bayesians end up teaching only one or two Bayesian courses. There is a bit more in Graduate Programs, but still very little.

A spectacular growth seems to be happening in applied areas, however. Demography, Pharmacology, animal breeding, genetics, ... etc., to name just a few of which I am aware of, are increasingly applying sophisticated state-of-the-art Bayesian methods. Others are increasingly asking for courses and updating on Bayesian methods. There is the big danger, however, that we, academics, do not appropriately interact with these extremely motivated areas, and this would be a pity and a big loss. I think the role that ISBA can play in this respect is very clear and important.

`7. What do you enjoy most about your work?`

Studying, reading, learning,

thinking about puzzling problems ... and meeting, chatting, interacting with people! Bayesians are great fun to be around, not only professionally, but also in social terms. We Mediterraneans have always enjoyed very much to "waste" time socializing with friends (although we have recently learnt that this is now called "developing the emotional intelligence", which certainly sounds much better!). I have made real good friends among Bayesians over the years. I really very much enjoy developing my emotional intelligence with such wonderful people!

`And least?`

I just hate bureaucracy. I find no intelligence whatsoever that I can develop in the middle of hordes of forms, papers, meetings, letters, reports, etc.! Unfortunately, and in spite of all my efforts, it seems that a rapidly increasing amount of my time is now hopelessly wasted in just that.

`8. What is your favorite statistics book?`

I can't decide between DeGroot's *Optimal Statistical Decisions* and Berger's *Statistical Decision Theory and Bayesian Analysis, 2nd edition*.

`9. As an ex-president of ISBA, what do you think is the purpose of the Society today? And what of its future? What are you looking forward to in Crete?`

There are, in the abstract, nice goals for ISBA to achieve. I think that ISBA should really lean towards facilitating exchange among Bayesians, all kind of Bayesians, specially those that are not in the "usual group". When I was President, I really intended to heavily promote the "interest groups" so as to attract applied people into it, provide a common "umbrella", and make it easier to contact each other, organize focused workshops, etc. I was thinking in particular of the Maxent group and of the Animal Breeders group to begin with. Unfortunately, I never even got to it! There were so many "little details to take care of!". ISBA is still shaky and undefined. It needs to dramatically increase the number of members, draw several bylaws and fix several details of its rules. A big issue is that of publications, since members do not really see any advantage in belonging to the Society (and people who are against Bayesian journals are already keeping themselves off ISBA just because of the possibility of a Bayesian journal anyway!). It is however a tricky issue, and we might lose some few stubborn members if we started a journal.

In Crete, I am really looking forward to the realization of an old "dream": namely to see a nice, "regular", well attended, widely representative ISBA meeting! I realize that Crete will be a success specially because of the great effort of the organizers and the scientific committee and others, and not so much because everyone now loves ISBA, but I am willing to be happy anyway! ... ah! and could I be a Bayesian and not to look forward to intensely developing my emotional intelligence? I do not think so! so, indeed, I am also looking very forward to see my old friends, hopefully make some new ones ... and enjoy the wonderful island!

`10. What do you think about your own future directions in Bayesian statistics, and about the future of Bayesian statistics in general?`

My own future directions? you must be joking! I am not even very sure what will be interesting me tomorrow! I had the suspicion that I will for a while lean toward applications, because I am seeing myself getting more and more curious about it, but I have no idea how long will this last. Also, with all this model checking business, I am also getting fairly curious about non-parametrics, and I might start reading and doing something in that regard (I am always most curious about what I am most ignorant!). I would not mind a revival of Decision Theory either (I am somehow worriedly seeing myself getting curious about it again!). I am still heavily puzzled by many modeling and model checking issues, specially in highly sophisticated, complicated models, so I think it likely that I will devote some effort in that direction ... but, as I said, who knows!

I would not like to say a thing about "the future of Bayesian statistics", and even less in writing! it is like this 1960's books that call themselves "modern approach to such-and-such": the sure way to

make a fool of myself! I have not anticipated any of the big changes of Bayesian Statistics before (I merely happily lived them) and there seems to be no indication that I should be able to foresee them now!

I "thank" you and Fabrizio for thinking about me to make this interview. This is the first one in my life (and I hope the last one too!). I very much sympathize with you for all the efforts you are devoting to the NL. It certainly is a great one! Congratulations! See all of you in Crete!

Many thanks to Susie for doing the interview, especially at short notice. I found her replies both thought–provoking and amusing in turns, and I hope you do too.

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Hersonissos, Crete

May 28-June 1 2000

PACK YOUR BAGS! THE BAYESIANS ARE GOING TO CRETE

by Alicia Carriquiry and Steve Fienberg
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Plans for ISBA 2000 progress at a fantastic clip. The local arrangements committee is hard at work and we are planning a wonderful array of social activities to complement the first-rate scientific program, the quality hotel and conference facilities, and the exotic surroundings. As of the middle of February, over 220 people have registered to attend the meetings. ISBA 2000 participants will come from over 25 countries around the world, and they will represent about 10 different disciplines, from statistics to medicine to economics to engineering and more. This interdisciplinary mix of experts at ISBA 2000 is just one more indication of the impact of the Bayesian approach outside of statistics.

For those who haven't yet registered, time is running out. You won't want to miss out on a terrific meeting. We will not be able to guarantee rooms in the conference hotels for those who register after April 20.

We have received almost 60 requests for travel funds from young researchers and students from around the world who are presenting their work in Crete. The Finance Committee of ISBA 2000 is hoping to decide on travel awards within end of March. We are waiting to hear official word from Eurostat and from the National Science Foundation regarding availability of travel funds before we do any allocation. If you submitted a request for funding, then you should be hearing from us by mid April.

A few other matters:

- If you are planning on registering on-site, please plan to bring enough cash to cover the cost of registration. We will be able to take credit card and check payments, but you may experience delays and some inconvenience if you decide to use your credit card to register upon arrival.
- Flight availability into Crete is becoming problematic, so please make your reservations soon.
- We will use our list of registrants to send a request for information as the conference date approaches. For example, we will request final arrival and departure information, so that we can pick you up at the airport or at the port.

We hope to see all of you in Crete! We will shortly begin posting news and information on a regular basis at the conference web site, Go to the ISBA web page: www.bayesian.org, and follow the clicks from ISBA 2000.

MCMC AND BAYESIAN DATA ANALYSIS: THE BEGINNING

by Alan E. Gelfand
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We present a brief review of the history of MCMC in Bayesian Statistics.

Stochastic simulation using Monte Carlo was not developed in the statistics community. For at least the past half century, scientists, primarily physicists and applied mathematicians, have sought to simulate the behavior of physical, chemical, and biological processes.

Sampling methods based upon Markov chains were first developed for applications in statistical physics where primary concern is with calculating properties of condensed matter systems.

Such systems are composed of enormous numbers of parts (atoms or molecules). These parts are usually all the same or of a small number of types so that modeling of the behavior of individual parts is straightforward. However, exact assessment of the overall properties of the system under such modeling is analytically infeasible. An alternative is to treat such systems stochastically, making probability statements about system behavior. In particular, for many such systems there is a notion of equilibrium. If we can simulate the system at equilibrium, we can learn about properties of the system when it is in equilibrium. To do so we model system transitions using a Markov chain whose limiting distribution is the stochastic model for the system at equilibrium. Hence, emerges the strategy of designing Markov chains to achieve a specified equilibrium distribution and then running trajectories of the chain to sample from this distribution, to learn about features of this distribution. Indeed, this is the seminal proposal of Metropolis, et al. (1953) which introduced what is now known as the Metropolis algorithm.

Interest in Markov chain sampling methods for applications in probability and statistics was encouraged by the influential paper of Geman and Geman (1984) which applied such methods to image restoration. Image analysis introduces an enormous number of variables, typically one for each pixel intensity. Geman and Geman drew an analogy between image analysis and statistical mechanics where pixel levels play the role of states of individual atoms or molecules in a real physical system. They introduced the computational algorithm which they called stochastic relaxation. In particular, working with a so-called Markov random field they noticed, given a particular neighborhood system, the equivalence of such a field to a joint Gibbs distribution over the variables in the field. They provided a stochastic relaxation algorithm to sample such a distribution which they therefore referred to as a Gibbs sampler.

The modeling framework for Geman and Geman was Bayesian. Starting with prior knowledge about the true image through a Markov random field specification, a blurred image is then observed and posterior updating with regard to the total image is the objective. Hence, Geman and Geman, through the Gibbs sampler, provide the first use of MCMC in Bayesian data analysis.

Meanwhile, the statistical physics community pursued extensions and variations of the Metropolis algorithm. This work is summarized in books such as Binder (1992). Statisticians contributed to this effort as well, notably Hastings (1970), Peskun (1973) and Besag (1974).

In 1990 Gelfand and Smith successfully demonstrated the applicability of the Gibbs sampler for fitting a broad range of Bayesian models. Previously, Tanner and Wong (1987) had introduced a special case of the Gibbs sampler, substitution sampling, under the name of data augmentation. Li (1988) also predates Gelfand and Smith, illustrating the use of the Gibbs sampler for multiple imputation. Clayton (1991) working in a random effects setting, proposed the Gibbs sampler concurrently with Gelfand and Smith. Perhaps, the most useful insight from Gelfand and Smith is the recognition that a Bayesian model (likelihood $\times$ prior) not only provides the joint posterior up to normalization but also all full conditional distributions, again up to normalization. This contrasts with the Geman and Geman setting where full conditional distributions are

simplified through a neighborhood system. The concern then is unique determination of the joint distribution from these conditionals but the nonnormalized joint distribution is never obtained.

Tierney (1994) presents an early theoretical unification of many of the stochastic simulation approaches. Nonetheless, subsequent writers debate whether the usual algorithmic implementation is "Metropolis steps with Gibbs sampling" or whether the Gibbs sampler is a special case of a "block-at-a-time" Metropolis-Hastings algorithm. Regardless, the crucial point is the replacement of the sampling of a high dimensional vector with the sampling of lower dimensional component blocks, thus breaking the curse of dimensionality.

The recognition of the potential of MCMC as a Bayesian model fitting tool arose serendipitously with the wide availability of inexpensive high speed computing, the latter fueling considerable experimentation with the former. Hence, the early '90's saw an unprecedented flurry of research activity with this new tool including probabilistic rigor, algorithmic refinement and broad application.

A workshop at Ohio State University in February 1991, "Bayesian Computation using Stochastic Simulation" brought together not only Bayesian researchers but stochastic simulation workers with interests in areas such as pattern recognition, artificial intelligence, and genetics. The "Night of the eleven Bayesians" (May 6, 1992) brought an unprecedented event to the Royal Statistical Society: three read papers on MCMC for Bayesian model fitting (Besag and Green, 1993; Gilks, et al., 1993; Smith and Roberts, 1993), arguably the last peak of activity in this area.

The excitement of those days in the early '90's has long since died down. Though work continues, as a research area we find stability. But the resultant revolutionary change in the nature of Bayesian data analysis and ensuing interdisciplinary outreach has forever altered the place of Bayesian inference within the statistical community.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. *J. Roy. Statist. Soc., B*, 36, 192-326.

Besag, J. and Green, P.J. (1993). Spatial statistics and Bayesian computation. *J.R. Statist. Soc. B*, 55, 25-37.

Binder, K. (1992). *The Monte Carlo Method in Condensed Matter Physics*. Springer-Verlag, Berlin.

Clayton, D.G. (1991). A Monte Carlo method for Bayesian inference in frailty models. *Biometrics*, 47, 467-485.

Gelfand, A.E. and Smith, A.F.M. (1990). Sampling based approaches to calculating marginal densities. *J. Amer. Statist. Assoc.*, 85, 398-409.

Geman, S. and Geman, D. (1984). Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Trans. Pattern Anal. Mach. Intell.*, 6, 721-741.

Gilks, et al. (1993). Modeling complexity: applications of Gibbs sampling in medicine. *J.R. Statist. Soc. B*, 55, 39-52.

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

Li, K.H. (1988). Imputing using Markov Chains. *J. of Statistical Computation and Simulation*, 30, 57-79.

Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H. and Teller, E. (1953). Equation of state calculations by fast computing machines. *J. of Chemical Physics*, 21, 1087-1092.

Peskun, P.H. (1973). Optimum Monte-Carlo sampling using Markov chains. *Biometrika*, 60, 607-612.

Smith, A.F.M. and Roberts, G.O. (1993). Bayesian computation via the Gibbs sampler and related Markov chain Monte Carlo methods. *J.R. Statist. Soc. B*, 55, 3-23.

Tanner, M.A. and Wong, W.H. (1987). The calculation of posterior distributions by data augmentation. *J. Amer. Statist. Assoc.*, 82, 528-540.

Tierney, L. (1994). Markov chains for exploring posterior distributions. *Ann. Statist.*, 22, 1701-1762.

TEMPLATE MIXTURE MODELS FOR IMAGE REGION ANALYSIS

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We use our Template Mixture Models to flexibly model binary regions in a population of images.

Here at the Johns Hopkins Medical Institutions, before an epileptic patient undergoes brain surgery to have their seizure focus removed, they are tested using a technique called Direct Cortical Electrical Interference (DCEI) to reduce the chance of the surgery causing a cognitive impairment. The aim of these tests is to give the surgeon an idea of where *not* to cut, regardless of the location of the seizure focus. Essentially, a grid of electrodes (approx. 8×8) is implanted directly on the surface of the brain, and subsequent cognitive tests are performed while electrical current is passed through any chosen two electrodes. The current is sufficient to numb the brain near the two electrodes, so a cognitive test failure indicates that the tested region of the brain is *necessary* for that task. Typical cognitive tests are to move one's tongue, or to name a stylized object shown on a computer monitor.

Up to now, the surgeon was given a map of those electrodes causing an impairment and those not, and they made a rough guess at where they should not cut. The first figure on the next page shows a dataset superimposed on a stylized outline of the side of the brain (ignoring for a moment the grey-scale contours). Bars without dots indicate electrode pairs not causing an impairment, and bars with dots indicate those which did cause an impairment. Diana Miglioretti, Scott Zeger, and I have recently been interested in modeling the surgeon's interpretation of this data to promote diagnosis objectivity and repeatability.

Another strong incentive to parametrically model this process is the possibility of combining information across images. For every patient that undergoes this kind of study, there are several other similar patients that have gone before them. Currently the surgeon ignores this previous information. The new patient's data is the only source used to infer where not to cut. Incorporating historical data can produce better region estimates for the patient at hand.

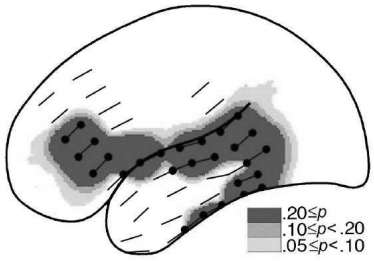
The data produced from DCEI testing is sparse binary measurements in the plane: the ability (or not) to perform the task when current is applied to a set of electrodes. Our goal is to use this data to automatically estimate the true associated *no-cut* region for the surgeon.

We know several characteristics of the process by which the binary data is produced. First, some work has been done using finite-element analysis to quantify the current envelope produced around the electrode pair. (The current does not travel directly from one electrode to the other because the brain is not a perfect conductor.) Second, the probability of an impairment is positively associated with the amount of current passing through the true necessary region. The neurologists tell us that even a small amount of current applied to the region should impair it. To model this binary data, we use a logistic regression where the independent variable is the amount of current passing through the necessary region (to be estimated).

On the other hand, we do not know very much about the shape of necessary regions. Neurologists believe that they should be smooth, rounded, and somewhat larger than the electrode spacing, but further information is not available for developing our prior distribution. Our *Template Mixture Model* is designed to implement these vague notions about the region shape, while remaining fairly non-informative otherwise. It is based on the simple idea that a wide variety of shapes can be created using only the union of a set of simple templates. For this application, we use circles as the templates, of unknown radius and position.

Furthermore, we do not specify the number of circles used to parameterize the necessary region. There is therefore an unknown number of parameters (the centers and radii of the circle templates), so we use Peter Green's Reversible Jump techniques to explore the combined parameter space of all possible numbers of templates.

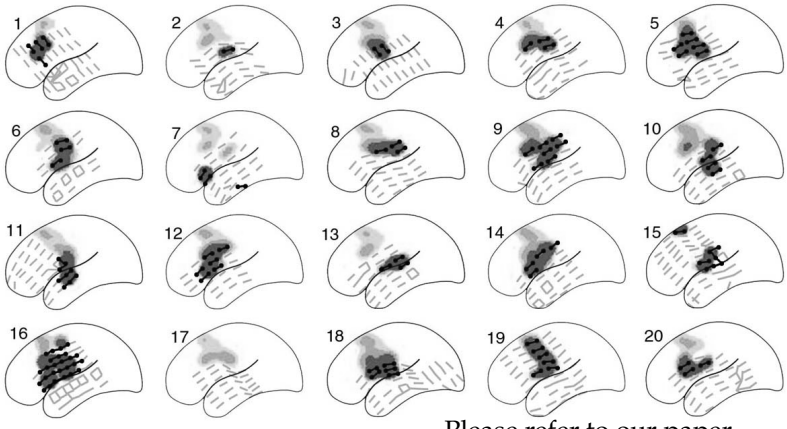
By averaging across a set of realizations of plausible regions given the data, we produce a map of posterior probabilities that give, for each location in the map, the posterior probability that the location is contained in the necessary region. In the following figure, we show this posterior probability (p) map for one patient taking a comprehension test. (In this test, a number of colored chips are placed on a tray in front of the patient, and s/he is asked to move a chip of a particular color.)



Using this visualization tool, the surgeon can make a more objective and informed decision about where not to cut. For instance, the low probability contour gives a conservative region estimate.

The real power of this technique becomes apparent when we begin to combine information across patients. We embed the one-patient model into a larger hierarchical model on a population of images. We assume that, for a specific task, there is a *population* necessary region, and each patient in the population must have a region similar to that population region. But significant differences in region shape can also exist in the population. We do this by specifying that, for there to be a template located in any image in the population, there must be an associated template in the population region. Conversely, each patient's region does *not* have to use every template in the population region. We achieve shrinkage in our estimates of individual regions by allowing patient regions to share population templates if they are close together. But if a patient dataset indicates a region very different than the rest of the population, the model produces new population templates specifically for that divergent patient's data.

The following figure shows our posterior probability map estimates for 20 patients performing the "tongue" task. (The patient is asked to stick out their tongue and, when electricity is applied, any involuntary tongue movement is considered an impairment.) Note the wide variety of regions modeled, while retaining similarity to the population.



Each patient's own data drives most of the fit, but where there is no information (i.e. outside the grid), the other patients in the population drive the estimation. For instance, patient 17 never showed an impairment in this task, but was not tested in the high regions where many others in the population did show an impairment. The model predicts patient 17's region could be up there, but is *not* closer to the fully-tested sylvian fissure (the middle horizontal curve) even though many others in the population were impaired there.

The method so far shows great promise in rendering more objective diagnoses as well as enabling image population modeling for better individual patient predictions. Automatic diagnosis is only the beginning of the possibilities for this model. For instance, we have examined questions like "Is syllable discrimination necessary for auditory comprehension?" by mapping both tasks' necessary regions and calculating the posterior probability that the former region is contained inside the latter region.

Please refer to our paper "Template mixture models for DCEI data" in an upcoming issue of *Biostatistics* for further information including references.

CLINICAL TRIALS

by Donald A. Berry
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Some thoughts on Bayesian approaches to clinical trials.

Bayesian approaches to clinical trials languished for many years, with a few staunch advocates jousting with windmills. The ideas were as neat and compelling as they are now, but applying them was not. There was much tradition against these radical notions and the tradition was hard to crack: a biostatistician once told me that every time he heard me speak he became a Bayesian . . . for 10 minutes!

Things have changed and they continue to change. I wish I could say that people started to listen to reason. Although reason may have played a role, the major sources of change lie elsewhere. One source is clearly the recent wonderful advances made in Bayesian computation: What we once said we could do in theory we can now do in practice.

Another impetus to change in the United States came from an unlikely source: The US Congress. By way of background, there are a few hundred drug companies in the world and a small number of them dominate the development process. But there are 10s of thousands of medical device companies. Drug companies can afford to spend many millions of dollars developing a drug, even if it will eventually be dumped. Other drugs make up for the loss. The consumer foots the bill for any inefficiencies in the process. Few medical device companies can operate this way. A device failure can mean that the company goes belly up.

If there is any constant in the medical device industry it is that there is no constant! Devices are continually being modified to make them work better. But previous versions were not that different. Shouldn't the companies be able to use historical information in the regulatory process? Congress said yes, albeit indirectly, in the 1997 Food and Drug Modernization Act. But how should one best use prior information in statistical inference? The rest, as they say, is history!

Under the leadership of Greg Campbell and Larry Kessler, the Biometrics unit of the Center for Devices and Radiological Health of the US FDA has played and is playing an important role in the legitimization of Bayesian biostatistics. They encourage Bayesian submissions for marketing approval. They are currently developing FDA guidelines to aid companies in deciding when Bayesian methods may be most appropriate. Actually, much of this work had begun before the 1997 Congressional initiative. There is a ripple effect throughout the biomedical world. Which brings me to drug studies. Why shouldn't a gigantic drug company want to save a few bucks while treating patients better? The potential efficiencies of using a Bayesian approach are not lost on such companies, and so the Bayesian bandwagon grows.

Dose-finding studies are but one example of settings in which the Bayesian approach is appealing to drug companies. But there is another reason that sensible designs such as what are called "continual reassessment methods" have come into vogue. The phase I designs they are replacing are clearly unethical and inefficient. It is hard to imagine that they came into being, never mind that they lasted as long as they did. Actually, the phase I, II, III trichotomy is artificial and has led to some bad practices in drug development. It is always a mistake to pretend you know something. For example, acting as though the optimal dose is known after phase II is folly. This attitude leads to most drugs being marketed at inoptimal doses.

Continued influences of far-sighted Bayesians in drug development will help smooth out this trichotomy. In particular, we will eventually pay explicit attention throughout the drug development process to learning about things we do not know, and we will design trials that recognize the need for such learning.

Interim and Final Analysis in Clinical Trials

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We focus on selected references to provide a sense of the extent of Bayesian applications in this area.

The following list is not meant to be exhaustive in any sense, and some important articles may have been unintentionally excluded from the list. Some articles promoting a Bayesian approach in Clinical trials are:

• D. A. Berry(1993). **A case for Bayesianism in clinical trials (with discussion)**. *Statistics in Medicine*, 12:1377-1404.

• J. M. Brophy, L. Joseph(1995). **Placing trials in context using Bayesian analysis. GUSTO revisited by Reverend Bayes.** *J. Ameri. Medical Assoc.*,15;273(11):871-5.

Also by the same authors:
Bayesian interim statistical analysis of randomised trials. *Lancet*, vol. 349, no. 9059: 1166-8.

Opposing comments on pp. 1168-9 of the same issue.

•L. S. Freedman, D. J. Spiegelhalter, M. K. Parmar(1994). **The what, why and how of Bayesian clinical trials monitoring.** *Statistics in Medicine*,13, no. 13-14, 1371-83; discussion 1385-9.

•J. B. Kadane(1995). **Prime time for Bayes**. *Control Clin Trials*, 16(5):313-8.

The following are some more recent writings promoting Bayesian approaches in Medical Statistics in general.

•F. Davidoff(1999). **Editorial: Standing Statistics Right Side Up.** *Annals of Internal Medicine*, 130, 1019-1021.

•S. N. Goodman (1999). **Toward Evidence-Based Medical Statistics 1: The P Value Fallacy.** *Annals of Internal Medicine*, 130, 995-1004.

•S. N. Goodman (1999). **Toward Evidence-Based Medical Statistics 2: The Bayes Factor.** *Annals of Internal Medicine*, 130, 1005-1013.

The following article provides Bayesian approaches to interim analysis along with references of earlier work.

•D.J. Spiegelhalter, L. S. Freedman, and M. K. B. Parmar(1994). **Bayesian approaches to randomized trials (with discussion).** *J. Roy. Statist. Soc., Ser. A*, 157, 357-416.

A more recent review paper is

•D. J. Spiegelhalter, J. P. Myles, D. R. Jones, and K. R. Abrams(2000). **Bayesian methods in health technology assessment.** To appear in *Health Technology Assessment*.

Another related article by the same authors is:
An introduction to Bayesian methods in health technology assessment. *British Medical Journal(Clinical Research Ed.)*, 1999,vol. 319, no. 7208: 508-12.

Several articles on the topic by D. Berry and D. Stangl and many others can be found in the book:

•**Bayesian Biostatistics** by D. Berry and D. Stangl(1996)(eds.), Marcel Dekker.

Some of the very early papers of interest are

•J. Cornfield(1966). **Sequential trials, sequential analysis and the likelihood principle.** *The American Statistician*, 20, 18–23.

•J. Cornfield(1966). **A Bayesian test of some classical hypotheses – with applications to sequential clinical trials.** *J. Amer. Statist. Assoc.*, 61, 577–594.

A case study of a clinical trial is presented in the article below, and the book following it covers many of the Bayesian approaches to clinical trials.

•B. P. Carlin, K. M. Chaloner, T. A. Louis, and F. S. Rhame(1995). **Elicitation, monitoring, and analysis for an AIDS clinical trial (with discussion).** In *Case Studies in Bayesian Statistics, Volume II*, eds. C. Gatsonis, J.S. Hodges, R.E. Kass and N.D. Singpurwalla, New York: Springer-Verlag, pp. 48-89.

•B. P. Carlin, and T. A. Louis(1996). **Bayes and Empirical Bayes Methods for Data Analysis**, Boca Raton, FL: Chapman and Hall/CRC Press. (Revised edition to appear, August 2000.)

The following articles involve development or application of Bayesian methodologies in interim and final analysis of Clinical Trials.

•E. Lazaridis and R. Gonin(2000). **A new program to compute and evaluate continuously monitored stopping boundaries for clinical trials.** *Computer Methods and Programs in Biomedicine*, 61, 3, pp 187-194.

In the above article, code for the calculation and evaluation of continuously monitored stopping boundaries for use in one-arm and two-arm clinical trials is given. It is written in S-Plus and requires both a C compiler and the S-Plus program. The code has been tested in UNIX and Microsoft Windows environments, and compiled code is available from the authors' website.

•R. SIMON AND L. S. FREEDMAN(1997). **Bayesian design and analysis of two x two factorial clinical trials.** *Biometrics*, 53(2):456-64.

Bayesian methods for the design and analysis of 2 x 2 factorial clinical trials are given in the above paper. These methods avoid the need to dichotomize one's assumptions that interactions either do or do not exist, and provides a flexible approach to the design and analysis of such clinical trials.

•J. B. GREENHOUSE(1992). **On some applications of Bayesian methods in cancer clinical trials.** Statistics in Medicine, vol. 11, no. 1:37-53.

Bayesian methods are discussed, and applied to a class of survival models for the analysis of survival times in the NCCTG trial, a randomized controlled clinical trial for the treatment of advanced colorectal carcinomatrial.

•J. B. GREENHOUSE AND L. WASSERMAN(1995). **Robust Bayesian methods for monitoring clinical trials.** *Statistics in Medicine*, 30;14(12):1379-91.

Application of Robust Bayesian methods to examples of clinical trials taken from the literature are given, along with an illustration of how these methods can be used to help a data monitoring committee decide whether or not to stop a trial early.

•B. P. CARLIN, J. B. KADANE AND A. E. GELFAND(1998). **Approaches for optimal sequential decision analysis in clinical trials** *Biometrics*,54(3):964-75.

A fully Bayesian approach including appropriate loss functions to interim and final analyses of clinical trial data is given. Forward sampling and backward induction approaches are presented and applied to data from a recent AIDS clinical trial.

•K. P. KLEINMAN, J. G. IBRAHIM AND N. M. LAIRD(1998). **A Bayesian framework for intent-to-treat analysis with missing data** *Biometrics*,54(1):265-78.

A longitudinal clinical trial where measurements are made after treatment drop-out on a random sample of subjects who drop the treatment is considered. A Bayesian approach to fitting a two-piece linear spline model is presented and applied to data that have no off-treatment observations.

•P. M. FAYERS, D. ASHBY AND M. K. PARMAR(1997). **Tutorial in biostatistics Bayesian data monitoring in clinical trials.** *Statistics in Medicine*, 16(12):1413-30.

A trial terminated early because of apparent treatment benefits might fail to influence sceptical clinicians to modify their treatment policy. Impact of the results of a clinical trial upon clinical practice is assessed using Bayesian methods. Uninformative, sceptical and enthusiastic priors are used and illustrated with interim analyses of a clinical trial in oesophageal cancer.

•B. P. CARLIN AND D. J. SARGENT(1996). **Robust Bayesian approaches for clinical trial monitoring** *Stat. Med.*, 15(11):1093-106.

Robustness of conclusions from interim and final analysis of a clinical trial to the prior specification is addressed, in order to convince a broad group of potential consumers. Various classes of priors are considered to characterize the class that would lead to a given decision. A dataset from an AIDS clinical trial is used to illustrate the method.

•P. F. THALL, R. M. SIMON AND E. H. ESTEY(1995). **Bayesian sequential monitoring designs for single-arm clinical trials with multiple outcomes.** *Statistics in Medicine*, 28;14(4):357-79.

Bayesian decision criteria and monitoring boundaries are presented for monitoring multiple outcomes in single-arm clinical trials, using a Dirichlet-multinomial model to accommodate general discrete multivariate responses.

The approach is illustrated with a variety of single-arm cancer trials. Practical extensions and applications of the method in the above article are given in the follow-up article below, with applications

to construct designs for phase IIA activity trials and phase II equivalence trials.

•P. F. THALL AND H. G. SUNG(1998.) **Some extensions and applications of a Bayesian strategy for monitoring multiple outcomes in clinical trials.** *Statistics in Medicine*,No. 14, V. 17 pp 1563 - 1580.

•B. FREIDLIN, E. L. KORN AND S. L. GEORGE(1999). **Data Monitoring Committees and Interim Monitoring Guidelines.** *Controlled Clinical Trials*, Volume 20, Issue 5: 395-407.

It is argued, in the above article, that study protocols should include monitoring guidelines with formal looks at each data monitoring committee meeting. Such guidelines are shown to reduce the average duration of a trial with negligible effect on power and estimation bias. Some monitoring guidelines require extreme evidence to stop a trial early and do not distinguish between stopping a trial during active accrual and follow-up stages. Practical solutions for these are proposed.

•D. A. BERRY, M. C. WOLFF AND D. SACK(1994). **Decision making during a phase III randomized controlled trial.** *Controlled Clinical Trials*, vol. 15, no. 5:360-78.

Bayesian approach and dynamic programming are used to continually assess the impact of a trial to prevent a disease on the health of the target population, and to make modifications including stopping the trial. An example is given which involves a vaccine trial for the prevention of haemophilus influenzae type b with the objective of minimizing the number of cases of this disease in a Native American population over a specified horizon.

•S. L. GEORGE, C. LI, D. A. BERRY AND M. R. GREEN(1994). **Stopping a clinical trial early: frequentist and Bayesian approaches applied to a CALGB trial in non-small-cell lung cancer.** *Statistics in Medicine*, vol. 13, no. 13-14: 1313-27.

This paper reviews the statistical and other considerations leading to decision to stop a phase III clinical trial for patients with stage III non-small-cell lung cancer, and presents later follow-up information on these patients. Some Bayesian alternatives to the standard frequentist approaches are explored. How these alternatives provide a natural way to address many of the issues raised in monitoring clinical trials is demonstrated.

•C. TSAI AND K. CHALONER(1999). **Using Prior Opinions to Examine Sample Size in Two Clinical Trials.** *Control Clin. Trials*,20:395-407.

For two large clinical trials involving the treatment of advanced HIV disease, the sample size for reaching consensus with high probability is calculated using prior opionions from over 50 HIV clinicians. Plots are given for determining parameter values for which a particular sample size is sufficient for consensus to be reached with high probability.

•G. L. ROSNER AND D. A. BERRY(1995). **A Bayesian group sequential design for a multiple arm randomized clinical trial.** *Statistics in Medicine*, 14(4):381-94.

In most group sequential designs in the literature, as the number of treatments increases, so does the probability of falsely rejecting the null hypothesis. A group sequential design for a proposed randomized clinical trial comparing four treatment regimens is discussed. It is shown that relatively simple posterior probability calculations, along with simulations to calculate power under alternative hypotheses, can produce appealing designs for randomized clinical trials.

•K. A. CRONIN, L. S. FREEDMAN, R. LIEBERMAN, H. L. WEISS, S. W. BEENKEN, AND G. J. KELLOFF(1999). **Bayesian monitoring of phase II trials in cancer chemoprevention.** *J. of Clinical Epidemiology*, vol. 52, no. 8 : 705-11. Comments and discussion on pp 713-716.

Frequentist performance of Bayesian interim analysis methods (Spiegelhalter et al. (1994)), which give greater flexibility and simplicity of inference to the monitoring of randomized controlled Phase II trials using intermediate endpoints, are investigated. Results suggest that the Bayesian approach to interim analysis is well suited for monitoring small randomized controlled Phase II chemoprevention trials for early detection of either inactive or promising agents.

SOFTWARE FOR FLEXIBLE BAYESIAN MODELING

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Software, developed at the University of Toronto, is reviewed by the author

This software is meant to support research and education regarding:

• Flexible Bayesian models for regression and classification based on neural networks and Gaussian processes, and for probability density estimation using mixtures. Neural net training using early stopping is also supported.

• Markov chain Monte Carlo methods, and their applications to Bayesian modeling, including implementations of Metropolis, hybrid Monte Carlo, slice sampling, and tempering methods.

These facilities might be useful for actual problems, but you should note that many features that might be needed for real problems have not been implemented, that the programs have not been tested to the extent that would be desirable for important applications, and that permission to use the software for free is granted only for purposes of research and education.

The complete source code (in C) is provided, allowing researchers to modify the program to test new ideas. It is not necessary to know C to use the programs (assuming you manage to install them correctly).

This software is designed for use on a Unix or Linux system, using commands issued to the command interpreter (shell). No particular window system or other GUI is required, but a plotting program will be very useful. I use the xgraph plot program, written by David Harrison, which allows plots to be produced by just piping data from one of the commands; it can be obtained from my web page.

➤ Markov chain Monte Carlo facilities

All the Bayesian models are implemented using Markov chains to sample from the posterior distribution. For the elaborate models based on neural networks, Gaussian processes, and mixtures, this is done by combining general-purpose Markov chain sampling procedures with special modules written in C. Other models could be implemented in the same way, but this is a fairly major project.

To allow people to play around with the various Markov chain methods more easily, a facility is provided for defining distributions (on R^n) by giving a simple formula for the probability density. Many Markov chain sampling methods, such as the Metropolis algorithm, hybrid Monte Carlo, slice sampling, and simulated tempering, may then be used to sample from this distribution. Bayesian posterior distributions can be defined by giving a formula for the prior density and for the likelihood based on each of the cases (which are assumed to be independent).

A long review paper of mine on "Probabilistic Inference Using Markov Chain Monte Carlo Methods" can be obtained from my web page. This review discusses methods based on Hamiltonian dynamics, including the "hybrid Monte Carlo" method. These methods are also discussed in my book on "Bayesian Learning for Neural Networks". My web page also has papers on slice sampling ("Markov chain Monte Carlo methods based on 'slicing' the density function") and on Annealed Importance Sampling, both of which are implemented in this software.

➤ Neural network and Gaussian process models

The neural network models are described in my thesis, "Bayesian Learning for Neural Networks", which has now been published by Springer-Verlag (ISBN 0-387-94724-8). The neural network models implemented are essentially as described in the Appendix of this book. The Gaussian process models are in many ways analogous to the network models. The Gaussian process models implemented in this software, and computational methods that used, are described in my technical report entitled "Monte Carlo implementation of Gaussian process models for Bayesian regression and classification", available from my web page, and in my Valencia conference paper on "Regression and classification using Gaussian process priors", in Bayesian Statistics 6. The

Gaussian process models for regression are similar to those evaluated by Carl Rasmussen in his thesis, "Evaluation of Gaussian Processes and other Methods for Non-Linear Regression", available from his web page, at `www.cs.utoronto.ca/~carl`; he also talks about neural network models. To understand how to use the software implementing these models, it is essential for you to have read at least one of these references.

The neural network software supports Bayesian learning for regression problems, classification problems, and survival analysis, using models based on networks with any number of hidden layers, with a wide variety of prior distributions for network parameters and hyperparameters. The Gaussian process software supports regression and classification models that are similar to neural network models with an infinite number of hidden units, using Gaussian priors.

The advantages of Bayesian learning for both types of model include the automatic determination of "regularization" hyperparameters, without the need for a validation set, the avoidance of overfitting when using large networks, and the quantification of uncertainty in predictions. The software implements the Automatic Relevance Determination (ARD) approach to handling inputs that may turn out to be irrelevant (developed with David MacKay).

For problems and networks of moderate size (eg, 200 training cases, 10 inputs, 20 hidden units), fully training a neural network model (to the point where one can be reasonably sure that the correct Bayesian answer has been found) typically takes up to several hours on a modern personal computer. However, quite good results, competitive with other methods, are often obtained after training for under an hour. The time required to train the Gaussian process models depends a lot on the number of training cases. For 100 cases, these models may take only a few minutes to train (again, to the point where one can be reasonably sure that convergence to the correct answer has occurred). For 1000 cases, however, training might well take a day.

The software also implements neural network training using early stopping, as described in my paper on "Assessing relevance determination methods using DELVE", in Neural Networks and Machine Learning, C. M. Bishop, editor, Springer-Verlag, 1998. A similar early stopping method is also described in Carl Rasmussen's thesis (see above).

➤ Bayesian mixture models

The software implements Bayesian mixture models for multivariate real or binary data, with both finite and countably infinite numbers of components. The countably infinite mixture models are equivalent to Dirichlet process mixture models. The sampling methods that I have implemented for these models are described in my technical report on "Markov chain sampling methods for Dirichlet process mixture models", which can be obtained from web page; see also my technical report on "Bayesian mixture modeling by Monte Carlo simulation".

The software implements the basic sampling operations for these models, but is rather preliminary in some respects, lacking many facilities that would be useful in practical applications.

➤ Examples

• Examples of Bayesian regression and classification models based on neural networks and Gaussian processes.

• Examples of Bayesian mixture models. Includes command files for the test in my paper on "Markov chain sampling methods for Dirichlet process mixture models".

• Examples of Markov chain sampling on distributions specified by simple formulas.

• Examples of Markov chain sampling for Bayesian models specified using formulas for the prior and likelihood.

• Examples of neural network survival models.

• Examples of neural network learning using gradient descent and early stopping.

• Command and data files used for the tests in my paper on "Annealed importance sampling".

One should note, however, that these examples do not constitute "recipes" that can be used unchanged for new

problems. They are intended to help you understand the models, priors, and computational methods, so that you can devise an appropriate way of handling whatever problem you are interested in.

➤ Portability of the software

The software is written in ANSI C, and is meant to be run in a UNIX environment. It is known to work on a Linux system (Redhat 6.0) with a Pentium processor, and on an SGI machine running IRIX Release 6.5. It also seems to run OK on a SPARC machine running SunOS 5, using the 'gcc' C compiler, and on DEC Alpha machines, provided that the -ieee and -std options are given to the DEC C compiler. As far as I know, the software does not depend on any peculiarities of these environments (except perhaps for the use of the drand48 pseudo-random number generator, and the lgamma function), but you may nevertheless have problems getting it to work in substantially different environments, and I can offer little or no assistance in this regard.

There is no dependence on any particular graphics package or graphical user interface. The 'xxx-plt' programs are designed to allow their output to be piped directly into the 'xgraph' plotting program, but other plotting programs can be used instead, or the numbers can be examined directly. The 'xxx-tbl' programs output the same information in a different format, which is useful when plotting or analysing data with S-Plus, since this format is convenient for the S-Plus read.table command.

TEACHING BAYESIAN STATISTICS IN THE SCIENTIFIC CURRICULA

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It is well known that the best way to learn something is to teach it. When I had to give the Laboratory of Physics course to Chemistry students and introduce elements of probability and statistics applied to data analysis, I did as most new teachers do: I started repeating what I had learned years before, more or less using the same lecture notes. This worked well for explaining the experiments, but when I moved to probability, the situation was quite embarrassing. In the very first lecture I realized that I was not convinced of what I was saying. I introduced probability as the ratio between favourable and possible cases, but I had no courage to add 'if the cases are equally probable'. I cheated by saying 'if the cases are equally possible' and moved rapidly to examples. The students had no time to react, the examples were well chosen, and I was able to survive that lesson and the following weeks.

The problem returned when we came to the evaluation of measurement uncertainty, a typical application of statistics in scientific disciplines. I had to acknowledge that the reasoning used in practice by physicists was quite in contradiction with the statistics theory we learn and teach. The result was that I had started the semester saying that subjective probability was not scientific, and ended it teaching probability inversion applied to physics quantities.

In the years since, I have clarified my ideas and, thanks also to the freedom allowed by the Italian university system, I have set up an introductory mini-course based on Bayesian concepts. Recently I have published an article (Am. J. Phys. 67, December 1999, pp.1260-1269) that gives a short account of the way I introduce subjective probability and Bayesian inference. The paper is also available on my web page, `www-zeus.roma1.infn.it/~agostini` together with other applications of Bayesian inference and teaching material. Here I would like to touch very briefly on some points in which other teachers might be interested.

University students have already developed, from high school, some negative reaction towards the words 'belief' and 'subjective' ("Science is objective!"). It is important, therefore, to clarify immediately the difference between belief and 'imagination', between subjective and 'arbitrary'. For the first pair of concepts I find Hume's analysis particularly convincing. For the second one I find crucial the role of de Finetti's coherent bet, without

which probability statements are, in my opinion, empty statements. I also find important to separate assessments of probability from decision issues (belief versus 'convenience').

The interplay of subjective probability with combinatorial and frequency-based evaluations is also an important point to be clarified soon. In particular, it is important to distinguish observed frequencies from expected frequencies. The former are statistical data and can be used to assess beliefs under well-specified conditions, whereas the latter are just a way to express the beliefs. Many scientists think they are frequentists because they are used to expressing their beliefs in terms of frequencies (but they also apply the same reasoning to probability of hypotheses and give a probabilistic interpretation of frequentistic coverage).

As far as the inferential aspects are concerned, I find it unavoidable to speak about probability of true values, i.e. of objects which are not directly observable and therefore, strictly speaking, not verifiable. I understand that it is possible to skip the intermediate state of the true values, and only speak about probability of future observations conditioned by past observations. But in practice it is not easy to follow strictly this approach. The scientific method is based on models for the real world and on making statements about the parameters of the model: Who has never 'seen' a mass, an electric charge or an angular momentum? What is important is to be consistent, and to always make a distinction between the things which are really observed and the 'metaphysical' objects. For example, it is important to clarify that it is possible to make a frequency distribution of an experimental observable (such as the reading of a scale) under apparently similar experimental conditions and use it to evaluate the probability distribution that we associate with the likelihood. In contrast, it is impossible to evaluate the probability distribution of true values by extrapolating from frequency distribution. The only way to assess their probability is to use Bayesian probability inversion.

Once the Bayesian inference is presented, it is important to show that many conventional methods can be recovered as limit cases of the Bayesian ones, under certain well-understood restricting conditions. The best example is the least square fit. The advantage is that the interpretation of the result corresponds to what scientists have anyway, and students are aware of the hidden hypotheses behind the methods. It is also important to show what are the implicit assumptions that make the conventional scheme of hypothesis test 'often to work', though it is not logically grounded. So, even p-values can be used to spot a possible problem, but certainly not to draw scientific conclusions or to take decisions.

ISBA/SBSS ARCHIVE FOR ABSTRACTS

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/`

NEW DIRECTIONS

by Maria De Iorio
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My name is Maria De Iorio and I am a Ph.D. student in ISDS, Duke University. I will be the Associate Editor of the ISBA newsletter's Student's Corner for this year. It has been a great pleasure being offered this opportunity. First of all I want to thank Fabrizio Ruggeri for this fantastic possibility. I am sure it will be a very interesting and fruitful experience for me. I have no experience in editorial work, so I hope you will forgive all the mistakes I might commit in the future.

Up to now the Student's Corner has mainly presented abstracts of dissertations (mostly Bayesian). While I plan to continue to present abstracts of new dissertations, I would also like to present different topics which, I believe, are interesting for all students. In particular, in the next issues I would like to touch on two specific themes. The first one concerns what kind of opportunities the market offers for "young statisticians": industry, academics, organizations, laboratories, financial institutions, etc..I think it would be nice also to publish articles describing personal experiences during job interviews. Moreover, I would like to profile several statistics programs: what kind of courses they offer, what type of research is conducted, and, broadly speaking, what kind of statistician they would like "to create".

Moreover I would like to open the Student's Corner to a frequentist perspective. From time to time a student will present challenging problems in frequentist statistics and discuss a possible solution, to explore the interface between the two approaches.

To accomplish these goals I will need help and collaboration from all of you. It is my intention to make the Student's Corner a place to exchange ideas and to hold constructive discussions about research and our problems of common interest.

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Statisticians in the Financial Industry

In general one of the nice things about being a statistician is the variety of possibilities we have to develop our professional careers in different areas. Whether it is in academia or industry, the flexibility of statistical sciences have allowed us to play key roles in most application areas in recent years. In particular, a major growth area in research and application of statistical modeling is in the financial industry. Many financial institutions have realized the need for statisticians to develop new models and techniques to explain and predict the economic environment and help into decision making process.

These needs have become even more evident due the recent globalization and integration of the economies worldwide, the more complex and developed investing mechanisms and the incredible growth of technology and telecommunications.

Research areas in many financial institutions represent a great opportunity for statisticians to blend theory and application in real life applications where the intellectual challenges are broad and exciting. In my short experience, I have witnessed the transition to new statistical modeling and computation and specifically the fast growth of Bayesian statistics in key areas of the finance industry. However, the evolution of Bayesian methodologies in this applied field is still in its initial stages and more research efforts need to be done to consolidate and expand the already successful techniques currently applied.

On the other hand, the job market in this field is pretty tight and competitive. Usually, we would have to highlight our quantitative and research oriented background to compete with economists and financial graduates and emphasize our applied, flexible and more practical skills to distinguish ourselves from mathematicians and physicists.

Job interviews are generally tough and with a high degree of variability. Depending on the area and position one maybe looking for they may ask explanations of theorems and models or even write computing programs on the spot. In some other departments they will just try to assess your

thinking process in combination with your language and communication skills. As with any other research job in academia or industry, it is fact that the opportunities and challenges are there for someone to take them and it is a reality that statisticians are in the radar screen of many financial institutions.

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Bayesian Inference in Hidden Linear Birth-Death Processes
Advisor: Dr. Peter Guttorp

This dissertation deals with the development of inferential tools for partially observed or hidden continuous time stochastic population processes. Even if a lot is known about the properties of stochastic population processes, we rarely see these models fit to data. However, many processes in biology, epidemiology, ecology, and physics are modeled as continuous time stochastic population processes. This can partly be due to not being able to observe such processes completely, so inference on the parameters of interest becomes very involved.

The reasons for observing the population only partially may be due to efficiency or to physical constraints, e.g. when the population of interest resides in a living body. In such a context only samples or subsets of the population may be observed at discrete times. For example, this is the situation that arises when studying hematopoiesis, the process of blood cell production, research that partially motivated this dissertation. The interest here is on having a better understanding of hematopoietic stem cell (HSC) kinetics. HSCs are primitive blood cells that support the entire blood and immune system.

This dissertation focuses on the problem of making inference in hidden linear birth-death processes, since a similar model, although somewhat more complicated, has been used to model HSC behavior. The process is hidden because only a probabilistic function of the birth-death process states is observable. The goal is to provide reasonable estimates of the birth and death rates.

A more classical approach to this inferential problem, that makes use of the Forward-Backward algorithm, does not provide a satisfactory solution. The two main reasons of its failure are: the infinite number of possible hidden states, and the fact that the hidden process is continuous in time while the observations are taken only at discrete times.

Using this approach involves the computation of transition probability matrices of large dimensions. Since we do not know how many states the hidden process visited during the observation period, we are forced to put a bound on the size of the state space. These transition probabilities are very unstable when the observation times are far apart and computationally expensive.

However, a Bayesian approach together with MCMC and reversible jump MCMC methods seems to overcome the problems stressed above and provide reasonable estimates for the parameters of interest. The developed algorithms, in principle, permit integration over the space of multivariate stochastic population processes.

This complex integration step, formerly a barrier to Bayesian inference in such a problem, allows the computation of posterior distributions for the parameters of interest conditioned on the observed data without restrictions on the hidden process. Simulation results show that the true parameter values fall in regions of high posterior probability. Identifiability issues are also discussed, challenging current experimental practice in hematology. The methods shown in this dissertation have great promise for solving an exciting problem in hematology.

Viridiana Lourdes de Leon
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Bayesian Analysis of Multivariate Futures in Energy Markets
Advisor: Dr. Mike West

The stochastic behavior of commodity prices plays a central role in modeling approaches to the evaluation of commodity-related securities. We develop models for commodity prices by exploiting the common latent structure of multiple time series of prices of futures contracts, based on traditional economic theories about the short-term and long-term behavior of spot prices and the relationship with futures contracts. We build on previous work of E. Schwartz and J. Smith (1998) in terms of basic model forms, and explore developments and analyses of oil future series.

This work involves a new class of Bayesian dynamic multivariate time series models for analyzing the latent structure of series of futures contract prices with different maturities. This class of models is based on two latent factor processes: a notional equilibrium price level, and a process representing short-term deviations from equilibrium levels. The idea is that movements in prices for long-maturity futures contracts provide information on equilibrium price levels whereas differences in prices between the short and long term contracts provide information on short-term variations in prices.

The structure of the model includes novel ideas on singular observational variance matrices that allow for general analyses regarding uncertainty about the rank of such matrices. A major component of this project is the development of customized MCMC simulation algorithms for model fitting and forecasting. We discuss current extensions to these models involving stochastic volatility components for latent processes and option pricing.

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A Generalized Predictive Criterion for Model Selection
Advisor: Dr. Fulvio Spezzaferri

This thesis presents a model selection criterion for the M-closed case (see Bernardo and Smith (1994)). The not exhaustive model class case is also briefly discussed. Given a set of parametric models, $\mathcal{M}$, that contains the true model and given a sample of independent observations from the true model, assume that the goal of the inference is to choose the model in $\mathcal{M}$ that gives the "best" estimate of the density of a future observation, $f_x(\cdot)$.

Following a decisional approach, we propose to take as state of the world the unknown density of the future observation and define the loss that we pay for estimating the true density $f_x(\cdot)$ with some distribution $P(\cdot)$ as a measure of discrepancy between $P(\cdot)$ and $f_x(\cdot)$. The model that minimizes the expected loss is then selected. In particular we propose to use as measure of discrepancy the class of α-divergences introduced by Csiszár (1967), Ali and Silvey (1966).

The corresponding model selection criterion, that we called *generalized predictive criterion*, has a straightforward interpretation as a function of posterior odds of the competing models and a term that takes into account the loss that we pay when we choose the wrong model. We show that this criterion is consistent and contains as a special case, using the Kullback-Leibler divergence, the predictive criterion of San Martini and Spezzaferri. We consider different examples in which both the true model and the estimate belong to the same location or scale family and we show that for these cases the class of α-divergences represents a reasonable class of loss functions, easy to interpret and general enough. Indeed we show that different choices of α allow us to formalize very different opinions about the loss that we accept for a generic estimate of the true density. However more work has to be done in this direction and more general results are needed.

The generalized predictive criterion is derived under the assumption that the true model is one of the models under comparison. Both the expected loss of each model and the model selection criterion strongly depend on this assumption. It can be shown, for example, that when this assumption is not satisfied the criterion can choose asymptotically the model which is farthest from the true model with respect to the α-divergence used. Asymptotically, in fact, the generalized predictive criterion is equivalent to the Bayes factor. As the number of observations increases the Bayes factor chooses with probability one the model in $\mathcal{M}$ which is closest to the true model with respect to the Kullback-Leibler divergence (Dmochowski, 1995), and so does the generalized predictive criterion.

However in general the α-divergences do not induce the same ordering among models, and the model closest to the true model in terms of Kullback-Leibler divergence might be the farthest from the true model with respect to another α-divergence and the incoherent behavior of the generalized predictive criterion is observed.

In general, however, we do not know whether the true model belongs to $\mathcal{M}$, unless $\mathcal{M}$

is the class of all possible models. Therefore we are forced to considerably enlarge the class $\mathcal{M}$. But the bigger is the class considered, the more complex are the models to compare, and the smaller is the discriminatory power of the selection criterion. As a possible compromise between needs of enlarging $\mathcal{M}$ and choosing between simple models, we might think to consider a bigger class of models, $\mathcal{M}'$ say, and then comparing the simple models in $\mathcal{M}$, assuming however that the true model belongs to $\mathcal{M}'$.

A previous work of Gutiérrez-Penã (1997) develops this idea using as measure of discrepancy the Kullback-Leibler divergence and defining the class $\mathcal{M}'$ as a Gaussian process centered on one of the competing models. We propose a generalization of these results using as measure of discrepancy a generic α-divergences and defining the class $\mathcal{M}'$ as a mixture of Gaussian processes centered on the competing models. This seems to us the most natural way to elicit the prior uncertainty about the true model. In addition for small sample size, centering only on one of the competing models (as in Gutiérrez-Penã 1997) we might favor, without any reason, the choice of that model.

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BAYESIANS IN NEW ZEALAND

by Renate Meyer
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There has been a long tradition of Bayesianism in New Zealand. Uptil John Deely's retirement a few years ago, the University of Canterbury has been its main and only stronghold. In the late 1960's, John Deely arrived at the University of Canterbury, and quickly established his research program in Bayesian statistics as the leader in New Zealand in this endeavor. Isolated at first with his own research interests and students, he was fortunate to arrange visits by Dennis Lindley, and eventually James Berger too, when his own research student, Murray Smith, joined him on the faculty. Dennis Lindley actually visited twice, once in 1976 then again in 1990. Also Jim Berger visited twice and during his first visit in 1985 some noteworthy students sat in on his lectures, namely John Horwood and Clive Loader. Finally Arnold Zellner visited Canterbury in 1995, jointly sponsored by the Maths and Economics Department.

By the late 1980's, as head of the statistics program, John Deely had hired Frank Lad, an operational subjectivist to join the faculty and expand the teaching program along subjective Bayesian lines. Frank attracted Erskine visits from James Dickey and Romano Scozzafava. Under John's supervision Kelly Mara did a PhD in 1979 entitled "Empirical Bayes with a changing prior", and next Howard Edwards did a PhD in 1980 entitled "Bayes Sequential Design Procedures: Theory and Applications". Canterbury's academic efforts were recognised through the Ph.D. thesis of Andrea Piesse, "Coherent Predictive Probabilities," which was honoured as a finalist in the Savage Award thesis competition in 1996. Andrea currently works at Statistics New Zealand in the Christchurch office. Other notable recent Bayesian theses were those of Phillip Schluter, "Identification of Hazardous Motor Vehicle Sites: Some Bayesian Considerations" in 1997, and "Some New Considerations for the Statistical Analysis of an Assay" by James O'Malley in 1999. Phillip currently works in the Department of BioStatistics at Queensland University, and James has a post-doctoral position in Biostatistics at the Harvard Medical School.

Unfortunately, John Deely's age cohort was the last to be affected by mandatory retirement at age 65 when New Zealand removed this requirement by legislation in the early 90's. So in December, 1996, John preempted the university by retiring to take up a position as professor of statistics at Purdue University, where he has been working actively since January, 1997.

Frank Lad, a consulting statistician in Canterbury, had completed his Ph.D. in econometrics at the University of Michigan in 1974, where he also earned an M.A. in Statistics. It was there he learned of subjective probability through his courses with Bruce Hill and William Ericson. After teaching for 10 years at the University of Utah, where his research focused on learning disabilities, a critique of fashionable economic theories of so-called "rational expectations", and of the reemergence of ideas of probability calibration, he spent one year in the Special Studies Section of the Federal Reserve Board of Governors. From there he spent two years at the SUNY Albany in a post-doctoral position where he collaborated with Jim Dickey and Mohammed Rahman. In 1988 he came to teach at the Canterbury University to work with John Deely. There he completed his major work, "Operational Subjective Statistical Methods: a mathematical, philosophical, and historical introduction" published by John Wiley in 1996. His main consulting during that era was in zoology, and he arranged practical consulting with honours students through connections with Fisher and Paykel, Bridgestone/Firestone, and Meadowfresh Dairies. When the Department of Mathematics and Statistics abruptly changed its direction after the retirement of John Deely, he saw the writing on the wall, and retired from the university as well the following year. He currently works as a statistical consultant, when he can spare time from his gardening, babysitting, golf, and bridge.

Apart from Canterbury, the Bayesian flag has been held up at Waikato University,

Hamilton, by Bill Bolstad since 1975. Bill first got interested in Bayes around 1967, when he was working at Lockheed, and realized the Kalman filter is just a linear application of Bayes theorem. Later in the early 1980's he got back to it when looking at Bayesian forecasting from Harrison-Stevens perspective. His current interests are in applied Bayesian statistics, particularly MCMC. He developed a first year Introduction to Bayesian Statistics course and has successfully delivered it at Waikato University. James Curran, a new appointment at Waikato and former Auckland graduate, is specialising in forensics using Bayesian methods. Tony Vignaux from Victoria University, Wellington, shares this research interest. Jointly with Bernard Robertson, Tony Vignaux published a book on "Interpreting Evidence" aimed at forensic scientists and lawyers. Tony is working on projects using maxent methods in scientific data analysis.

Also located in Hamilton but at Ruakura Agricultural Research Center, Martin Upsdell has been working on Bayesian smoothers. This grew out of his consulting work at the New Zealand Ministry of Agriculture and Fisheries, now AgResearch which involved fitting phosphate response curves to fertilizer data. He had this in mind when he completed a PhD degree in 1985 at Nottingham University under Adrian Smith, submitting a thesis entitled "Bayesian Inference for functions". Returning to New Zealand, he was eager to put his new-found solution to the test on consulting problems at AgResearch. He developed a freely available smoothing package called Flexi to expedite the application of smoothers.

Graham McBride from NIWA (National Institute of Water and Atmospheric Research) has worked in aquatic environmental science for over 25 years. His interest in Bayesian methods is rather recent and springs mostly from his dissatisfaction with the way classical results are often used and misinterpreted in environmental science, i.e. "I didn't get $p < 5\%$, I therefore infer no difference". He is enamoured of the harmony between what many scientists do (updating their understandings about bundles of hypotheses in the light of new data) and Bayesian approaches.

Rod Ball works in ForestResearch as a statistician supporting research aimed at relating properties of trees/logs/wood to products. He is also involved with the genomics group with statistics for gene mapping, and with statistics for entomology, plant diseases (generalised linear models and extensions), and sensory science (experimental design). One theme of his research is the applications of model selection in Bayesian hierarchical models.

Auckland University recently recruited one of the "leftover" Bayesians from Canterbury: Murray Smith joined the Engineering Department three years ago and is strongly associated with the Statistics Department. Other Aucklanders with strong Bayesian leanings are Russell Millar, Geoff Nicholls, David Scott, and myself, all new appointments made within the last six years. Russell and I have developed Bayesian state-space models for fisheries stock assessments. Apart from fisheries modeling, I am working on Bayesian nonparametric survival analysis in collaboration with Francois Perron (Montreal, CA), on Bayesian gravitational radiation data analysis with Nelson Christensen (Physics, Carleton College, USA), and stochastic volatility models for financial time series with Jun Yu (Econometrics, Auckland). David Scott's major research interest is in Markov chain Monte Carlo methods with applications to Bayesian analysis, particularly of categorical data, and rates of convergence of Markov chains.

In work with Colin Fox (Math, Auckland, NZ) Geoff Nicholls is looking at physics-based observation models of non-linear imaging processes, in particular, acoustic and impedence imaging. With Caitlin Buck (History, Cardiff, UK) and Martin Jones (Anthropology, Auckland, NZ), Geoff is exploring models of simple cultural processes for prior specification in radiocarbon date analyses. In collaboration with Jesper Moller (Math, Aalborg, Denmark) he has been designing perfect simulation algorithms for sample based Bayesian inference. New application areas entail prior and observation model building

from physics. Such unrestrained model building often leads to hard sampling problems. It is this which motivates his interest in Monte Carlo algorithms.

Acknowledgement: I would like to thank Frank Lad for providing detailed information about the Bayesian history at Canterbury and all the other Bayesian kiwis that kindly sent me their contributions.

NEWS FROM THE WORLD

by Antonio Pievatolo
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✻ *denotes an ISBA activity*

➤ Events

Bayesianism 2000. *May 11 and 12, 2000, King's College, London, UK.*

A conference on philosophical aspects of Bayesianism and its use in artificial intelligence. Web page: `http://www.kcl.ac.uk/ip/jonwilliamson/2000/bayesianism_2000.htm`.

Third IMA Conference on Quantitative Modelling in the Management of Health Care. *September 5-7, 2000, University of Salford, UK.*

The conference of the Institute of Mathematics and its Applications will focus on practical methodologies in budgeting, financing, setting of priorities, and allocation of resources for the provision of services, and the formulation and measurement of performance indicators. Papers covering experience with established methodologies and issues relating to their implementation are welcome together with those describing new methodologies. The conference will consist of keynote speeches, contributed papers and an exhibition of software. A special issue of the Health Care Management Science Journal contained papers presented at the conference in 1997. Deadline for abstract submission: May 1, 2000. Web page: `http://www.ima.org.uk`.

Third International Workshop on Objective Bayesian Methodology. *September 21-23, 2000, Ixtapa, Mexico.*

Objective Bayesian methodology is of increasing importance today for at least two reasons. First, application of Bayesian analysis is rapidly growing among nonspecialists, most of whom seek automatic or objective Bayesian procedures. Second, computational advances have allowed Bayesian methodology to be employed in problems of such complexity that determination of serious subjective priors is essentially impossible.

The Scientific Programme will feature at least 12 invited lectures, followed by invited discussions and by discussion from the floor.

Contributed papers are welcome; submit abstracts by May 31. These will be presented in two plenary poster sessions, organized in the tradition of the Valencia meetings.

Web page: `http://www.dpye.iimas.unam.mx/tameb`.

Analytical and Stochastic Modelling Techniques. *September 28-30, 2000, Hamburg, Germany.* Methods of stochastic modelling based on analytical and approximate results for Markov and semi-Markov stochastic processes, queueing networks, Petri nets, etc. have recently become increasingly popular.

In many fields of applications involving performance and reliability modelling of discrete flow systems, it has been widely recognized that analytical and approximate approaches in stochastic modeling can successfully complement simulation methods.

In many models, methods based on analytical or approximate analytical results are more preferable comparatively to methods of direct stochastic simulation, because in general they save the time of computation and give possibility to obtain analytical dependencies of parameters.

Submit your abstract by April 30. Web page: `http://www.informatik.uni-hamburg.de/TIS/ESS2000.html`.

Second Workshop on Bayesian Inference and Stochastic Processes.

The workshop (following the one in Madrid, 1998) is being organised in Northern Italy, in May 24 to 27, 2001. Contact person: Fabrizio Ruggeri (fabrizio@iami.mi.cnr.it).

Third International Symposium on Sensitivity Analysis and Model Output. *June 18-20, 2001, Madrid*.

SAMO investigates the relative importance of model input parameters on model predictions. Sensitivity Analysis (SA) is usually linked to uncertainty analysis, which aims at characterising the uncertainty on the output as a result of uncertainties on the model inputs. SA techniques can be applied in many areas of knowledge and disciplines where models and computer experiments are present (physics, chemistry, environmental sciences, nuclear and industrial safety,economics, etc.). SA can be used for model calibration, verification, identification selection, quality-assurance, and in mechanism reduction. This symposium intends to bring together researchers and practitioners from different disciplines involved in theoretical aspects and practical applications of General sensitivity analysis, to share the latest developments in the area. Send abstracts by September 15, 2000. Web page: `http://www.ciemat.es/convocatorias/eventos/samo2001/samo_2001.html`.

Workshop on Bayesian nonparametrics. *July 27 to August 2, 2001 University of Michigan, Ann Arbor*.

Contact persons: Paul Damien (pdamien@umich.edu) in Canada and the USA, and Stephen Walker (s.walker@ic.ac.uk) in Europe.

➤ Awards and Prizes

✻ **Fourth Mitchell Prize.** The winner will be announced at ISBA 2000.

➤ Research Opportunities

Innovation in Clinical Research.

At the University of Texas M.D. Anderson Cancer Center, Professor Berry is setting up a Center for Innovation in Clinical Research. A goal of this center is to aid in the development and implementation of creative designs for dose-finding and other medical trials. Another goal is to teach Bayesian statistics and the use of Bayesian methods to drug and device industry workers.

➤ Miscellanea

BayesX, a new software.

A new public-domain software package called BayesX has been developed which analyses Bayesian versions of generalized additive models, models for spatial correlation, varying coefficient models and various combinations of those.

This is very useful software for a variety of applications where parameters are a priori correlated. A major advantage of the software is that it performs block updates in order to have good convergence and mixing properties of the MCMC algorithm.

BayesX runs under Windows only; a Unix version is planned for the future. To read a description and download the software go to `http://www.stat.uni-muenchen.de/~lang/bayesx/bayesx.html`

Probability, unmasked?

Philosopher Foster Lindley attacks the foundations of statistics, when he says that probability violates the Aristotelian principle of excluded middle. He writes: "Although the so-called foundations of probability are admittedly mushy, it is, by far, the most ingenious of the equivocal languages. With it, speakers can speak more or less affirmatively, that is, affirm by degrees. This equivocation has permitted various ideological groups to advance views that would otherwise be considered ridiculous. Contenders for control of the language have included the classical, the limited frequency and the subjective, or Bayesian, interpretations". Meet him at `http://www.o-c-s.com/probability_unmasked/` (he welcomes feedback).

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