// INDIAN BAYESIAN SOCIETY

NEWS LETTER

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# From the desk of Professor Ghosh

I have been wondering what new things to do for the newsletter. Last year there was a suggestion that we encourage members to send personal news that would be of interest to other Bayesians. One could write about one's technical problems, a new Bayesian course or report a promotion or new recruitment. Hope some of you will start doing this soon, the sooner the better. I will set this going by writing of recent Bayesian events at ISI.

I have been teaching Bayesian topics in our Advanced Inference course for M. Stat for a long time. This course focusses on foundational questions and theoretical issues. But recently there is a new Bayesian course also at the M. Stat level with much more stress on methods and computation. I seem to recall it was created because many students were interested in such a course. In addition Bayesian topics are taught in our B. Stat. course.

These are not the only things. A new unit/department has been created by the Director ISI for bringing together statisticians interested in Bayesian and Interdisciplinary Research. Hopefully there will be some Bayesian activity as part of ISI's Platinum Jubilee celebrations.

On the international scene the most interesting event is the Valencia-ISBA conference in June this year. We hope to publish the program. This year, it reads like a quick-guided tour of new questions, new answers, leading to new methods, new computational challenges, new theory, etc. This is Valencia 8 with all the gusto of Valencia 1.

I end this short editorial with an anecdote that I heard from Jim Berger a few days ago. He told this true story to his class of freshmen, who thought it was cool. Alan Greenspan is the economist who was in charge of the Federal Reserve Board for monetary policy in the US and is believed to have kept the US economy safe for the last twenty years under many different Presidents. He has just retired. He was asked by the Wall Street Journal how he managed it. He just said, " Because I'm a Bayesian"!

Punardarshanaya cha.

– J.K. Ghosh

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# Statistics, Statisticians and Science

Arnold Zellner
University of Chicago, USA

When Dr. Upadhyay invited me to contribute to your Bayesian Newsletter, I wrote to him that "One issue that has been on my mind for many years is the relationship between statistics and the other sciences and how best to encourage fruitful interactions among all the sciences, perhaps within the context of our ISBA organization." In this connection, it is relevant to point out that formerly ISBA had a Council of Sciences, chaired by Professor Seymour Geisser and then by Professor Donald Berry, both outstanding statisticians that did much to foster fruitful interactions between statisticians and other scientists. Perhaps it is worthwhile to consider reactivating the Council of Sciences and to have it provide guidance to those who wish to establish new sections of ISBA. See the ISBA home page, http://www.bayesian.org for procedures for proposing new sections of ISBA. Note that the American Statistical Association (http://www.amstat.org) has many successful sections in the areas of biostatistics, business and economic statistics, Bayesian statistical science, sports, etc., operating under the guidance of a Committee on Sections. The sections sponsor journals, other publications, meetings, awards, etc. and have been very successful. Perhaps establishing a wide range of ISBA sections representing statistics and statisticians in many important areas of science and applications on an international scale would be similarly successful.

It is of course well known that statistics and statisticians have played an important role in the development of many sciences. As Karl Pearson recognized many years ago,

"The unity of all science consists alone in its method, not in its material. The man [or woman] who classifies facts of any kind whatever, who sees their mutual relation and describes their sequences, is applying the scientific method and is a man [or woman] of science." [Pearson, K. (1938), The Grammar of Science, London: Everyman, 1938, p.16].

This Unity of Science Principle is an important unifying concept that should be generally appreciated and emphasized. Further, Sir Harold Jeffreys, a famous natural scientist, who wrote his classic book, Theory of Probability (Oxford U. Press, Classics Series, 1998, reprint of the 3rd revised edition, 1967, first edition, 1939) to instruct his fellow scientists how to analyze and draw conclusions from their data, explains that,

"The fundamental problem of scientific progress, and a fundamental problem of everyday life is that of learning from experience. Knowledge obtained in this way is partly merely of what we have already observed, but part consists of making inferences from past experience to predict future experience. This part may be called generalization or induction. It is the most important part; events that are merely described and have no apparent relation to others may as well be forgotten, and in fact usually are."

Thus, producing and learning from data and using them to formulate and implement models that explain the past and help predict and possibly control the future are central, important activities in all areas of science, be it biology, medicine, business, economics, sports, etc. Statisticians have contributed importantly to the production of good data by their work on the design of experiments, surveys, censuses and other data production procedures. As regards learning from data, emphasized by Jeffreys above as being a "fundamental problem," it is the case that he and many others recommend use of Bayes' Theorem as a fundamental model for learning from data, that is for solving estimation, testing, prediction and decision problems. Note that in non-Bayesian approaches, analysts do not use a formal model for learning from data and thus learn informally and "subjectively," many times in a non-reproducible fashion. Much research has shown that the Bayesian learning model, Bayes' Theorem, has performed well in solving estimation, testing, prediction, control and many other problems in many areas of science (see, e.g., the listing of Bayesian texts and monographs on the ISBA website, http://www.bayesian.org. Also in Zellner, A.(2004), Statistics, Econometrics and Forecasting: The Sir Richard Stone Lectures , Cambridge U. Press, pp. 23-38, 12 basic Bayes-non-Bayes issues are systematically discussed with the conclusion that it pays to go Bayes.)

A most important area of science is that of testing alternative hypotheses, models or theories, say ether drift versus no ether drift or Newton's laws versus Einstein's laws, or a positive effect of a drug versus no effect or a negative effect, etc. In each of these testing problems, Bayesians can and have associated probabilities with alternative hypotheses to express their degrees of belief or confidence in their validity and used Bayes' Theorem to compute how the information in data changes their initial probabilities or degrees of belief in alternative hypotheses and to obtain new probabilities that along with loss functions or structures can be employed to act optimally in choosing between or among alternative hypotheses. As Jeffreys and others emphasize, non-Bayesians use concepts of probability, e.g. frequentist concepts, that do not permit them to associate probabilities with degrees of belief in hypotheses and thus they can not employ prior and posterior odds in evaluation of alternative hypotheses or models. (See H. Jeffreys, Theory of Probability, cited supra, and the R.A. Fisher Lecture by James O. Berger, entitled, "Could Fisher, Jeffreys and Neyman Have Agreed on Testing?," Statistical Science, 18,1 (2003), 1-32, with invited discussion, for more on alternative approaches to testing.) It is also interesting to note that S.J. Press in his recently published Bayesian text writes at the end of his chapter on hypothesis testing as follows: "The Bayesian (Jeffreys) approach is now the preferred method of comparing scientific theories…Richard Feynman [a leading physicist] suggests that to compare contending theories in physics one should use the Bayesian approach." (p.230 of S.J.Press (2003), Subjective and Objective Bayesian Statistics: Principles, Models, and Applications," New York: Wiley.)

Thus in the area of testing alternative hypotheses or models, as well as in combining models, estimation, prediction, control, etc., Bayesian methods and results have been shown to compare very favorably with alternative methods in many areas of science. In view of these developments, an obvious, important opportunity exists for ISBA members to bring these findings to the attention of workers in many fields by showing them how to solve their problems more effectively by use of Bayesian methods.

In summary, I believe that the time is ripe for ISBA members to intensify efforts to establish links between ISBA and various sciences and areas of application, say by forming ISBA Sections. These Sections, operating under the guidance of an ISBA Council of Sciences can be very effective in showing others how to get better solutions to their new and old problems by use of appropriate Bayesian methods. Also, such interactions will undoubtedly involve innovations and production of new Bayesian methods that will make us all more productive and provide better solutions to our scientific and other societal problems.

# Isn't Everyone a Bayesian?

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"It is their straightforward, natural approach to inference that makes them [Bayesian methods] so attractive." (Schmitt, 1969)

## Introduction

Many statistical users misinterpret the p-values of significance tests as "inverse" probabilities: 1 - p is "the probability that the alternative hypothesis is true".

*"In these conditions [a p-value of 1/15], the odds of 14 to 1 that this loss was caused by seeding [of clouds] do not appear negligible to us." (Neyman et al., 1969)*

As is the case with significance tests, the frequentist interpretation of a 95% confidence interval involves a long run repetition of the same experiment: in the long run 95% of computed confidence intervals will contain the "true value" of the parameter; each interval in isolation has either a 0 or 100% probability of containing it. Unfortunately treating the data as random even after observation is so strange this "correct" interpretation does not make sense for most users. Ironically it is the interpretation in (Bayesian) terms of "a fixed interval having a 95% chance of including the true value of interest" which is the appealing feature of confidence intervals. Moreover, these "heretic" misinterpretations of confidence intervals (and of significance tests) are encouraged by most statistical instructors who tolerate and even use them. For instance Pagano, in a book that claims the goal of "understanding statistics", describes a 95% confidence interval as *"an interval such that the probability is 0.95 that the interval contains the population value". Pagano (1990, page 288)*

This dualistic conception was already present in Bernoulli (1713), who clearly recognized the distinction between probability ("degree of certainty") and frequency, deriving the relationship between probability of occurrence in a single trial and frequency of occurrence in a large number of independent trials.

Assigning a frequentist probability to a single case event is often not obvious, since it requires imagining a reference set of events or a series of repeated experiments in order to get empirical frequencies. Unfortunately, such sets are seldom available for assignment of probabilities in real problems. By contrast the Bayesian definition is more general: it is not conceptually problematic to assign a probability to a unique event (Savage, 1954; de Finetti, 1974).

Clearly, the Bayesian definition can serve to describe "objective knowledge", in particular based on symmetry arguments or on frequency data. So Bayesian statistical inference is not less objective than frequentist inference. It is even the contrary in some contexts.

Statistical inference is typically concerned with both known quantities - the observed data - and unknown quantities - the parameters and the data that have not been observed. In the frequentist inference all probabilities are conditional on parameters that are assumed known. This leads in particular to:

• significance tests, where the parameter value of at least a parameter is fixed by hypothesis;

• confidence intervals.

In the Bayesian inference parameters can also be probabilized. This results in distributions of probabilities that express our uncertainty:

• before observations (they does not depend on data): prior probabilities;

• after observations (conditional on data): posterior (or revised) probabilities;

• about future data: predictive probabilities.

As a simple illustration, let us consider a situation involving a finite population of size twenty with a dichotomous variable success/failure and a proportion φ of success. Hence the unknown parameter is φ. A sample of size five has been observed giving the known data as:

$$\boxed{0 \quad 0 \quad 0 \quad 1 \quad 0} \qquad f = \frac{1}{5}$$

The inductive reasoning is fundamentally a generalization from a known quantity -here the data f = 1/5 - to an unknown quantity - here the parameter φ.

## The frequentist approach: from unknown to known

In the frequentist framework, we have no probabilities and consequently no possible inference. So frequentist inference must reverse the situation. However, we have no more probabilities ... unless we fix a parameter value. Let us assume for instance φ = 0.75.

Then we get sampling probabilities Pr(f | φ = 0.75) – that is frequencies – involving imaginary repetitions of the observations. They can be obtained by simulating repeated drawing of samples of five marbles (without replacement) from a box that contains 15 black and 5 white marbles. Alternatively, they can be (exactly) computed from a hypergeometric distribution. These sampling probabilities serve to define a significance test. Given the data in hand (f = 1/5), if the null hypothesis is true (φ = 0.75), one finds in 99.5% of the repetitions a value greater than the observation (f > 1/5, the proportion of black marbles in the sample) for which the null hypothesis φ = 0.75 is rejected ("significant test": p = 0.005). Note that I do not enter here in the one-sided/two-sided test discussion that is irrelevant for my purpose.

However, this conclusion is based on the probability of the samples that have not been observed, what Jeffreys (1998/1939) ironically expressed in the following terms:

*"A hypothesis that may be true may be rejected because it has not predicted observable results that have not occurred."*

As another example of null hypothesis, let us assume φ = 0.50. In this case, if the null hypothesis is true (φ = 0.50), one finds in 84.8% of the repetitions a value f > 1/5, greater than the observation, for which the null hypothesis φ = 0.50 is not rejected by the data in hand. Obviously this does not prove that φ = 0.50!

Now a confidence interval can be constructed as the set of possible parameter values that are not rejected by the data. Given the data in hand we get the following 95% confidence interval: [0.05, 0.60]. How to interpret the confidence 95%? The frequentist interpretation is based on the universal statement:

"Whatever the fixed value of the parameter is, in 95% (at least) of the repetitions the interval that should be computed includes this value."

But this interpretation is very strange since it does not involve the data in hand!

## The Bayesian approach: from known to unknown

Let us return to the inductive reasoning, starting from the known data, and adopting a Bayesian viewpoint. We can now use, in addition to sampling probabilities, probabilities that express our uncertainty about all possible values of the parameter. In the Bayesian inference, we consider, not the frequentist probabilities of imaginary samples, but the frequentist probabilities of the observed data Pr(f = 1/5 | φ) for all possible values of the parameter. This is the likelihood function that is denoted by:

$$l(j \mid data)$$

We assume prior probabilities Pr(φ) before observations. Then, by a simple product, we get the joint probabilities of the parameter values and the data:

$$\begin{aligned}\Pr(j \ and \ f = 1/5) &= \Pr(f = 1/5 \mid j) \times \Pr(j) \\ &= l(j \mid data) \times \Pr(j)\end{aligned}$$

The sum of the joint probabilities gives the marginal predictive probability of the data, before observations:

$$\Pr(f = 1/5) = \sum_{j} \Pr(j \ and \ f = 1/5).$$

The result is very intuitive since the predictive probability is a weighted average of the likelihood function, the weights being the prior probabilities. And finally we compute the posterior probabilities after observations, by a simple application of the definition of conditional probabilities. The posterior distribution is simply the normalized product of the prior and the likelihood:

$$\begin{aligned}\Pr(j \mid f = 1/5) &\propto l(j \mid data) \times \Pr(j) \\ &= \frac{\Pr(j \ and \ f = 1/5)}{\Pr(f = 1/5)}.\end{aligned}$$

We can conclude with Berry:

*"Bayesian statistics is difficult in the sense that thinking is difficult." (Berry, 1997)*

In fact, it is the frequentist approach that involves considerable difficulties due to the mysterious and unrealistic use of the sampling distribution for justifying null hypothesis significance tests and confidence intervals. Frequent questions asked by students and statistical users show us that this use is counterintuitive: "why one considers the probability of samples outcomes that are more extreme than the one observed? "; "why must one calculate the probability of samples that have not been observed? "; etc. Such difficulties are not encountered with the Bayesian inference: the posterior distribution, being conditional on data, only involves the sampling probability of the data in hand, via the likelihood function $l(j \mid data)$ that writes the sampling distribution in the natural order: "from unknown to known".

## What should be Bayesian inference for experimental data analysis?

The most common criticism of the Bayesian approach by frequentists is the need for prior probabilities.

*"A common misconception is that Bayesian analysis is a subjective theory; this is neither true historically nor in practice" (Berger, 2004, page 3).*

The frequentist statistical inference is self-proclaimed "objective" contrary to the Bayesian inference that should be necessary "subjective". This claim is reinforced by the fact that many Bayesians place emphasis on a subjective perspective, in which the scientific inference should incorporate information external to the data – and even in some "extremist" views (Savage, 1954), personal opinions.

*"But the primary aim of a scientific experiment is not to precipitate decisions, but to make an appropriate adjustment in the degree to which one accepts, or believes, the hypothesis or hypotheses being tested," (Rozeboom, 1960).*

Moreover, by their insistence on the decision-theoretic elements of the Bayesian approach, many authors have obscured the contribution of Bayesian inference to experimental data analysis and scientific reporting. This can be the reason why until now scientists have been reluctant to use Bayesian inferential procedures in practice for analysing their data.

*1. "A major goal of statistics (indeed science) is to find a completely coherent objective Bayesian methodology for learning from data. This is exemplified by the attitudes of Jeffreys (1938/1961) and Jaynes (2003).*

*2. Objective Bayesian analysis is the best method for objectively synthesizing and communicating the uncertainties that arise in a specific scenario, but is not necessarily coherent in a more general sense.*

*My general view is that 1) is not attainable; 2) is often attainable and should be done if possible," (Berger, 2004, page 2).*

Without dismissing the merits of the decision-theoretic viewpoint, it must be recognized that there is another approach which is just as Bayesian, developed by Jeffreys in the thirties (Jeffreys, 1998/1939). Following the lead of Laplace (1986/1825), this approach aimed at assigning the prior probability when "nothing" was known about the value of the parameter. In practice, these non-informative prior probabilities are vague distributions that, a priori, do not favour any particular value. Consequently they let the data "speak for themselves". In this form the Bayesian paradigm provides, if not objective methods, at least reference methods, fully justified and appropriate for situations involving scientific reporting.

*"A successful objective Bayes theory would have to provide good frequentist properties in familiar situations for instance, reasonable coverage probabilities for whatever replaces confidence intervals," (Efron, 1998).*

Furthermore, even if it is not always made explicit, these methods aim to conciliate the Bayesian theory with the frequentist conception.

*"A widely accepted objective Bayes theory, which fiducial inference was intended to be, would be of immense theoretical and practical importance," (Efron, 1998).*

In order to promote them, it seemed important to us to give them a more explicit name than "standard", "non-informative", "reference" or "conventional". We call them fiducial Bayesian (B. Lecoutre, in Rouanet et al., 2000; Lecoutre, Lecoutre & Poitevineau, 2001; Lecoutre, 2006). With a similar perspective, Berger (2004) advocates to call them objective Bayes:

*"The statistics profession, in general, hurts itself by not using attractive names for its methodologies, and we should start systematically accepting the 'objective Bayes' name before it is co-opted by others," (Berger, 2004, page 3).*

## The current state of the use of statistical inference

I will now briefly discuss the current state of the use of statistical inference. Experimental research is facing a paradoxical situation. On the one hand, Null Hypothesis Significance Testing (NHST) is required in most scientific publications as an unavoidable norm and often appears as a label of scientificness. But on the other hand, NHST leads to innumerable misinterpretations and misuses. Furthermore, the most eminent and most experienced scientists, both on theoretical and methodological grounds, have explicitly denounced its use.

Today is a crucial time because we are in the process of defining new publication norms for experimental research. While users' uneasiness is ever growing, changes in reporting experimental results, especially in presenting and interpreting effect sizes, are more and more enforced within editorial policies in all fields.

## Common misinterpretations of NHST

Several empirical studies emphasized the widespread existence of common misinterpretations of NHST among students and scientists (for a review, see Lecoutre, Lecoutre & Poitevineau, 2001). Recently, Haller and Krauss (2001) found out that most methodology instructors who teach statistics to psychology students, including professors who work in the area of statistics, share their students' misinterpretations. Furthermore, Lecoutre, Poitevineau and Lecoutre (2003) showed that professional applied statisticians from pharmaceutical companies are not immune to misinterpretations of NHST, especially if the test is non-significant.

If some of the above results could be interpreted as an individual's lack of mastery, this explanation is hardly applicable to professional statisticians. More likely these results reveal that NHST does not address questions that are of primary interest for the scientific research. Thus, users must resort to a more or less nave mixture of NHST results and other information. In other words, they must make "judgmental adjustments" or "adaptative distorsions" (M.-P. Lecoutre, in Rouanet et al., 2000) designed to make an ill-suited tool fit their true needs.

So the confusion between statistical significance and scientific significance illustrates such an adjustment and can be seen as an adaptative abuse. The improper use of non-significant results as "proof of the null hypothesis" is again more illustrative. Indeed, faced with a non-significant result, users seem to have no other choice but to either interpret it as proof of the null hypothesis or attempt to justify it by citing an anomaly in the experimental conditions or in the sample.

We cannot accept that future statistical inference methods users will continue using non-appropriate procedures *because they know no other alternative*.

## A set of recipes and rituals

They are currently many attempts to remedy the inadequacy of usual significance tests (see for instance the recommendations of the Task Force of the American Psychological Association: Wilkinson et al., 1999; American Psychological Association, 2001). In particular, the necessity of reporting effect size estimates and their confidence intervals is stressed. The role of the planning of experiments (how many subjects to use) is also emphasized and power computations are recommended. In fact, these attempts are both partially technically redundant and conceptually incoherent. Just as NSHT, they should result in teaching a set of *recipes and rituals* – power computations, p-values and confidence intervals – without supplying *a real statistical thinking*. In particular, one can be afraid that statistical users continue to focus on the statistical significance of the result (only wondering whether the confidence interval includes the null hypothesis value) rather than on the full implications of confidence intervals.

## Confidence intervals and the duplicity of statistical instructors

Confidence intervals could quickly become a compulsory norm in experimental publications. In practice, two probabilities can be routinely associated with a specific interval estimate computed from a particular sample.

- The first probability is "the proportion of repeated intervals that contain the parameter". It is usually termed the coverage probability.
- The second probability is the Bayesian "posterior probability that this interval contains the parameter", assuming a non-informative prior distribution.

In the frequentist approach it is forbidden to use the second probability while in the Bayesian approach, the two probabilities are valid. Then the debates can be expressed on these terms: "whether the probabilities should only refer to data and be based on frequency or whether they should also apply to parameters and be regarded as measures of beliefs".

*"It would not be scientifically sound to justify a procedure by frequentist arguments and to interpret it in Bayesian terms," (Rouanet, in Rouanet et al., 2000, page 54).*

For many reasons due to their frequentist conception, confidence intervals can hardly be viewed as the ultimate method. Indeed their appealing feature is the result of a fundamental misunderstanding. It is undoubtedly the natural (Bayesian) interpretation of confidence intervals in terms of "a fixed interval having a 95% chance of including the true value of interest" which is their appealing feature. Ironically these heretic interpretations are encouraged by the duplicity of most statistical instructors who tolerate and even use them.

## Won't the Bayesian choice be unavoidable?

We then naturally have to ask ourselves whether the "Bayesian choice" will not, sooner or later, be unavoidable. So, training students and researchers in Bayesian methods should become an attractive challenge for statistical instructors. I argue that the sole effective strategy against the misuses of frequentist procedures is a smooth transition towards the Bayesian paradigm. The suggested strategy is to introduce Bayesian methods as follows.

- To present natural Bayesian interpretations of significance tests outcomes to call attention about their shortcomings.
- To create as a result of this the need for a change of emphasis in the presentation and interpretation of results.
- Finally to equip users with a real possibility of thinking sensibly about statistical inference problems and behaving in a more reasonable manner.

The desirability and the feasibility of this strategy are illustrated in Lecoutre (2006); the following points are outlined and discussed.

- Since most people use "inverse probability" statements to interpret NHST and confidence intervals, the Bayesian definition of probability, conditional probabilities and Bayes' formula are already – at least implicitly – involved in the use of frequentist methods. Which is simply required by the Bayesian approach is a very natural shift of emphasis about these concepts, showing that they can be used consistently and appropriately in statistical analysis.
- It is better - at least in a first stage - to focus the teaching on "objective Bayesian analysis", based on non-informative priors, avoiding the issue of assessing a subjective prior distribution. Indeed, insofar as experimental data analysis is concerned, it is not a good strategy to draw the attention of students (or researchers) on an approach that does not answer their expectations. Once the students will become familiarized with the use and interpretation of this objective Bayesian analysis, the introduction of "informative" prior distributions at a later stage is easier. There are appealing ways to introduce them. In particular, it is attractive to investigate the impact of a *handicap* ("skeptical") prior and to examine if the data give sufficient evidence to counterbalance it. Priors that express the results of previous experiments are also generally well accepted.
- With the Bayesian approach, intuitive justifications and interpretations of procedures can be given. Moreover, an empirical understanding of probability concepts is gained by applying Bayesian procedures, especially with the help of computer programs.

*"Students [exposed to a Bayesian approach] come to understand the frequentist concepts of confidence intervals and P values better than the students exposed only to a frequentist approach," (Berry, 1997).*

- Bayesian methods allow users to overcome usual difficulties encountered with the frequentist approach. In particular, using the Bayesian interpretations of significance tests and confidence intervals in the natural language of probabilities about unknown effects comes quite naturally to students. In return the common misuses and abuses of NHST appear to be more clearly understood. In particular students become quickly alerted that non-significant results cannot be interpreted as "proof of no effect".
- Bayesian predictive procedures give users a very appealing method to answer essential questions such as: "how big should be the experiment to have a reasonable chance of demonstrating a given conclusion?"; "given the current data, what is the chance that the final result will be in some sense conclusive, or on the contrary inconclusive?" These questions are unconditional in that they require consideration of all possible value of parameters. Whereas traditional frequentist practice does not address these questions, predictive probabilities give them direct and natural answer.

## Conclusion

In conclusion, the Bayesian approach is both desirable and feasible and fulfills the requirements of scientists. Moreover, it fits in better with their spontaneous interpretations of data than frequentist procedures. Nowadays Bayesian routine methods for the familiar situations of experimental data analysis are easy to implement and to learn. They offer promising new ways in statistical methodology. The Bayesian philosophy emphasizes the need to think hard about the information provided by the data in hand ("what do the data have to say?") instead of applying ready-made procedures. Users' attention can be focused to more appropriate strategies such as consideration of the practical significance of results and the replication of experiments.

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# Valencia / ISBA Eighth World Meeting on Bayesian Statistics

Benidorm (Alicante, Spain)

June 1st to June 6th, 2006

**Universitat de València, Spain**

**International Society for Bayesian Analysis**

# Scientific Programme (Selected Sessions)

## 1. Postgraduate Tutorial Seminar

The Conference will be preceded by three 2h30m long tutorials, intended to provide a short review of the main ideas in Bayesian Statistics. The tutorials will be delivered by members of the programme committee.

**Thursday, June 1st**

**10h00-12h30**: Tutorial 1

- **Dawid, A. Philip*** (University College London) [dawid at stats.ucl.ac.uk]
  **Bernardo, José M.*** (Universitat de València, Spain) [jose.m.bernardo at uv.es]
  *Foundations: Subjective and Objective Bayesian Statistics*

**14h30-17h00**: Tutorial 2

- **West, Mike*** (Duke University, USA) [mw at stat.duke.edu]
  **Heckerman, David*** (Microsoft Research, USA) [heckerma at microsoft.com]
  *Bayesian Modelling and Computation*

**17h30-20h00**: Tutorial 3

- **Bayarri, Susie*** (Universitat de València, Spain) [susie.bayarri at uv.es]
  **Berger, James, O.***(Duke University, USA) [berger at stat.duke.edu]. *Bayesian Model Assessment, Testing and Selection*

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## *2.Valencia 8 Invited Programme*

**Friday, June 2nd**

**09h00-09h25**: *Opening ceremony*

**09h30-11h00**: Session 1. *Bayes factors*

*Chair:* **Geweke, John** (University of Iowa, USA)

- **Raftery, Adrian E.*** (University of Washington, USA) [raftery at stat.washington.edu]
  **Newton, Michael A.** (University of Wisconsin, USA) [newton at stat.wisc.edu]
  **Satagopan, Jaya, M.** (Memorial Sloan-Kettering Cancer Center, USA) [satagopj at mskcc.org]
  **Krivitsky, Pavel N.** (University of Washington, USA) [pavel at stat.washington.edu]
  *Estimating the integrated likelihood via posterior simulation using the harmonic mean identity*
  *Discussant:* **Polson, Nicholas** (University of Chicago, USA) [ngp at gsb.uchicago.edu]

- **Rousseau, Judith** (Université de Paris Dauphine and CREST, France) [Rousseau at ceremade.dauphine.fr].
  *Approximating interval hypothesis: p-values and Bayes factors.*
  *Discussant:* **Petrone, Sonia** (Univ. Bocconi, Italy) [sonia.petrone at uni-bocconi.it]

**11h30-13h00**: Session 2. *Foundations*

*Chair:* **George, Edward** (Univ. of Pennsylvania, USA)

- **Schack, Rüdiger** (Royal Holloway, Univ. of London, UK) [r.schack at rhul.ac.uk]
  *Bayesian probability in quantum mechanics*
  *Discussant:* **Helland, Inge** (University of Oslo, Norway) [ingeh at math.uio.no].

- **Mira, Antonietta*** (Univ. dell'Insubria, Italy) [antonietta.mira at uninsubria.it].

  **Baddeley, Adrian** (University of Western Australia, Australia) [adrian at maths.uwa.edu.au]
  *Deriving Bayesian and frequentist estimators from time-invariant estimating equations: a unifying approach*
  *Discussant:* **Smith, Richard L.** (University of North Carolina, USA) [rs at stat.unc.edu].

**Saturday, June 3rd**

**09h30-11h00**: Session 3. *Priors on function spaces*

*Chair:* **Schmidt, Alexandra** (Universidade Federal do Rio de Janeiro, Brazil)

- **Gamerman, Dani*** (Universidade Federal do Rio de Janeiro, Brazil) [dani at im.ufrj.br]
  **Salazar, Esther** (Universidade Federal do Rio de Janeiro, Brazil) [esalazar at dme.ufrj.br]
  **Reis, Edna** (Universidade Federal do Rio de Janeiro, Brazil) [edna at dme.ufrj.br]
  *Dynamic Gaussian process priors, with applications to the analysis of space-time data.*
  *Discussant:* **Fuentes, Montserrat** (North Carolina State University, USA) [fuentes at stat.ncsu.edu].

- **Gelfand, Alan*** (Duke University, USA) [alan at stat.duke.edu]
  **Guindani, Michele** (M. D. Anderson Cancer Center, USA)[mguindani at mdanderson.org]
  **Petrone, Sonia** (Università Bocconi, Italy)[sonia.petrone at uni-bocconi.it]
  *Bayesian nonparametric modelling for spatial data analysis using Dirichlet processes*
  *Discussant:* **Hjort, Nils** (University of Oslo, Norway) [nils at math.uio.no].

**11h30-13h00**: Session 4. *Robust and objective Bayesian inference*

*Chair:* **Fienberg, Stephen** (Carnegie-Mellon Univ., USA)

- **Little, Roderick** (Univ. of Michigan, USA) [rlittle at umich.edu]
  **Zheng, Hui** (Massachusetts General Hospital, USA)
  *The Bayesian approach to the analysis of finite population surveys*
  *Discussant:* **Ruggeri, Fabrizio** (CNR-IMATI Milano, Italy) [fabrizio at mi.imati.cnr.it].

- **Sun, Dongchu*** (Virginia Tech, USA) [sund at vt.edu]
  **Berger, James. O.** (Duke University, USA) [berger at stat.duke.edu]
  *Objective priors for a multivariate normal model*
  *Discussant:* **Liseo, Brunero** (Università di Roma "La Sapienza", Italy) [brunero.liseo at uniroma1.it]

**Sunday, June 4th**

**09h30-11h00**: Session 5. *Genomics and proteomic*

*Chair:* **Richardson, Sylvia** (Imperial College School of Medicine, UK)

- **Holmes, Chris*** (Oxford University, UK) [c.holmes at stats.ox.ac.uk]
  **Pintore, Alexandre** (Oxford University, UK) [pintore at stats.ox.ac.uk]
  *Exploring low-dimensional structure in high dimensional data via Bayesian relaxation*
  *Discussant:* **Kohn, Robert** (University of New South Wales, Australia) [R.Kohn at unsw.edu.au]

- **Schmidler, Scott** (Duke University, USA) [schmidler at stat.duke.edu]
  *Bayesian shape classification with applications to structural proteomics*
  *Discussant:* **Wilkinson, Darren** (University of Newcastle Upon Tyne, UK) [d.j.wilkinson at ncl.ac.uk]

**11h30-13h00**: Session 6. *Model selection*

*Chair:* **Hans, Chris** (The Ohio State Univ., USA)

- **Chakrabarti, Arijit** (Indian Statistical Inst., India) [arijit_v at isical.ac.in]
  **Ghosh, Jayanta*** (Purdue University, USA) [ghosh at stat.purdue.edu]
  *Some aspects of Bayesian model selection for prediction*
  *Discussant:* **Lauritzen, Steffen** (University of Oxford, UK) [steffen at stats.ox.ac.uk]

- **Girón, Javier*** (Universidad de Málaga, Spain) [fj_giron at uma.es]
  **Moreno, Elías** (Universidad de Granada, Spain) [moreno at ugr.es]
  **Casella, George** (University of Florida, USA) [casella at stat.ufl.edu]
  *Objective Bayesian analysis of multiple change points for linear models*
  *Discussant:* **Rueda, Raúl** (UNAM, Mexico) [pinky at sigma.iimas.unam.mx]

**Monday, June 5th**

**09h30-11h00**: Session 7. *Bayesian computation*

*Chair:* **Roberts, Gareth** (Lancaster Univ., UK)

- **Del Moral, Pierre** (Université de Nice, France) [delmoral at math.unice.fr]
  **Doucet, Arnaud*** (University of British Columbia, Canada) [arnaud at stat.ubc.ca]
  **Jasra, Ajay** (Cambridge University, UK) [aj308 at cam.ac.uk]
  *Sequential Monte Carlo for Bayesian computation*
  *Discussant:* **Lopes, Hedibert** (University of Chicago, USA) [hlopes at ChicagoGSB.edu]

- **Skilling, John** (Maximum Entropy Data Consultants Ltd, UK) [skilling at eircom.net]
  *Nested sampling for general Bayesian computation*
  *Discussant:* **Evans, Michael** (University of Toronto, Canada) [mevans at utstat.utoronto.ca]

**11h30-13h00**: Session 8. *Latent feature models and multiple testing*

*Chair:* **MacEachern, Steven** (Ohio State Univ., USA)

- **Ghahramani, Zoubin*** (University of Cambridge, UK) [zoubin at eng.cam.ac. uk]
  **Griffiths, Thomas L.** (Brown University, USA) [tom_griffiths at brown.edu]
  **Sollich, Peter** (Kings College London, UK) [peter.sollich at kcl.ac.uk]
  *Bayesian nonparametric latent feature models*
  *Discussant:* **Dunson, David** (Duke University, USA) [dunson at stat.duke.edu]

- **Müller, Peter*** (University of Texas, USA) [pmueller at mdanderson.org]
  **Parmigiani, Giovanni** (Johns Hopkins University, USA) [gp at jhu.edu]
  **Rice, Kenneth** (University of Washington, USA)[kenrice at u.washington.edu]
  *FDR and Bayesian decision rules*
  *Discussant:* **Fearn, Tom** (University College London, UK) [tom at stats.ucl.ac.uk]

**Tuesday, June 6th**

**09h30-11h00**: Session 9. *Computer vision and function representation*

*Chair:* **van der Linde, Angelika** (University of Bremen, Germany)

- **Bishop, Christopher** (Microsoft Research Cambridge, UK) [cmbishop at microsoft. com]
  **Lasserre, Julia** (University of Cambridge, UK)
  *Generative or discriminative? Getting the best of both worlds*
  *Discussant:* **Lee, Herbert** (University of California, Santa Cruz, USA) [herbie at soe.ucsc.edu]

- **Clyde, Merlise*** (Duke University, USA) [clyde at stat.duke.edu]
  **Wolpert, Robert L.** (Duke University, USA)[rlw at stat.duke.edu]
  *Bayesian modelling with overcomplete representations*
  *Discussant:* **Vidakovic, Brani** (Georgia Institute of Technology, USA) [brani at isye.gatech.edu]

**11h30-13h00**: Session 10. *Genetics*

*Chair:* **Mortera, Julia** (Università di Roma 3, Italy)

- **Brooks, Stephen*** (Univ. of Cambridge, UK) [s.p.brooks at statslab.cam.ac.uk]
  **Manolopoulou, I.** (University of Cambridge, UK) [I.Manolopoulou at statslab.cam.ac.uk]
  **Emerson, B. C.** (Univ. of East Anglia, UK)
  *Assessing the affect of genetic mutation: A Bayesian framework for determining population history from DNA sequence data*
  *Discussant:* **Mallick, Bani** (Texas A&M University, USA) [bmallick at stat.tamu.edu]

- **Merl, Daniel** (University of California, Santa Cruz, USA) [daniel at ams.ucsc.edu]
  **Prado, Raquel*** (University of California, Santa Cruz, USA) [raquel at ams.ucsc.edu]
  *Detecting selection in DNA sequences:*

*Bayesian Modelling and Inference*
*Discussant:* **Vannucci, Marina** (Texas A&M University, USA) [mvannucci at stat.tamu.edu]

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### *3. ISBA selected plenary talks*

A set of 32 twenty-five minute plenary contributed oral presentations have been selected by the ISBA Conference Programme Committee, which will take place in the afternoons.

The ISBA Conference Programme Committee comprises the following: Kerrie Mengersen (Australia, co-chair), Peter Müller (USA, co-chair), Herbie Lee (USA, co-chair Finance), Jose M. Bernardo (Spain, past Chair; Valencia Programme Committee), Richard Arnold (New Zealand), Cathy Chen (Taiwan), Merlise Clyde (USA), Yanan Fan (Australia), Subashis Ghosal (USA), Paolo Giudici (Italy), Antonietta Mira (Italy), Paul Mostert (South Africa), Josemar Rodrigues (Brazil), Judith Rousseau (France), Fabrizio Ruggeri (Italy), Mark Steel (UK), Robert Wolpert (USA) and Jiangsheng Yu (China).

**Friday, June 2nd**

**17h00-18h40**: Session 1. *Bioinformatics and biostatistics*

*Chair:* **Mira, Antonietta** (Università dell'Insubria, Italy)

- **Vannucci, M.*** (Texas A & M, USA) [mvannucci at stat.tamu.edu]
  **Kim, S.** (Texas A & M, USA)
  **Tadesse, M.** (University of Pennsylvania, USA)
  *Bayesian variable selection in clustering via Dirichlet process mixture models*

- **Suchard, M. A.*** (University of California at Los Angeles, USA) [msuchard at ucla.edu]
  **Redelings, B. D.** (University of California at Los Angeles, USA)
  *Solutions to fundamental difficulties in evolutionary reconstruction: Joint Bayesian estimation of alignment and phylogeny*

- **Beal, M. J.*** (State University of New York at Buffalo, USA) [mbeal at cse.Buffalo.edu]
  **Teh, Y .W.** (National University of Singapore, Singapore)
  **Krishnamurthy, P.** (State University of New York at Buffalo, USA)
  *Clustering gene time series data with countably infinite hidden markov models: An application of the hierarchical Dirichlet process*

- **Jirsa, L.** (Czech Academy of Sciences, Czech Republic)
  **Quinn, A.*** (Trinity College Dublin, Ireland) [aquinn at tcd.ie]
  **Varga, F.** (Charles University, Czech Republic)
  *Identification of thyroid gland activity in radiotherapy*

**19h10-20h50**: Session 2. *Savage Prize Finalists*

*Chair:* **Clyde, Merlise** (Duke University, USA)

- **Choi, T.** (University of MD Baltimore County, USA) [tchoi at math.umbc.edu]
  *Posterior consistency in nonparametric regression problems using Gaussian process priors*

- **Nicoloutsopoulos, D.** (University College London, UK) [dimitris at stats.ucl.ac.uk]
  *Bayesian non-parametric estimation of copulas*

- **Xu, X.** (Ohio State University, USA) [xinyi at stat.ohio-state.edu]
  *Estimation of high dimensional predictive densities*

- **Amzal, B.*** (Novartis, Switzerland) [billy.amzal at novartis.com]
  **Bois, F.** (ENGREF, France)
  **Parent, E.** (INERIS, France)
  **Robert, C.P.** (Université de Paris Dauphine, France)
  *Bayesian optimal design via particle algorithms*

**Saturday, June 3rd**

**17h00-18h40**: Session 3. *Spatial and temporal inference*

*Chair:* **Mengersen, Kerrie** (Queensland University of Technology, Australia)

- **Fearnhead, P.*** (Lancaster University, UK) [p.fearnhead at lancaster.ac.uk]
  **Papaspiliopoulos, O.** (Lancaster University, UK) [o.papaspiliopoulos at lancaster.ac.uk]
  **Roberts, G.** (Lancaster University, UK) [g.o.roberts at lancaster.ac.uk]
  *Particle filters for partially observed diffusions*

- **Paez, M.S.*** (Universidade Federal do Rio de Janeiro, Brazil) [marina at im.ufrj.br]
  **Diggle, P.** (Lancaster University, UK)
  *Cox processes in time for point patterns and their aggregations*

- **Banerjee, S.** (University of Minnesota, USA)
  **Carlin, B.*** (University of Minnesota, USA) [carli002 at umn.edu]
  *Bayesian wombling*

- **Roberts, G.*** (Lancaster University, UK) [g.o.roberts at lancaster.ac.uk]
  **Beskos, A.** (Lancaster University, UK)
  **Fearnhead, P.** (Lancaster University, UK)
  **Papaspiliopoulos, O.** (Lancaster Univ., UK)
  *Bayesian inference for diffusions without discretisation*

**19h10-20h50**: Session 4. *Non-parametric and flexible inference*
*Chair:* **Ruggeri, Fabrizio** (CNR-IMATI Milano, Italy)

- **Chipman, H. A.** (Acadia University, Canada)
  **George, E.*** (University of Pennsylvania, USA) [edgeorge at wharton.upenn.edu]
  **McCulloch, R. E.** (University of Chicago, USA)
  *BART: Finding low dimensional structure in high dimensional data*

- **Griffin, J.*** (University of Warwick, UK) [J.E.Griffin at warwick.ac.uk]
  **Steel, M.** (University of Warwick, UK)
  *Nonparametric inference in time series problems*

- **Geweke, J.** (University of Iowa, USA) [john-geweke at uiowa.edu]
  *Bayesian modeling of conditional distributions*

- **Short, Margaret*** (Los Alamos National Laboratory, USA) [mbshort at lanl.gov]
  **Higdon, D. M.** (Los Alamos National Laboratory, USA) [dhigdon at lanl.gov]
  **Kronberg, P. P.** (University of Toronto, Canada) [kronberg at physics.utoronto.ca]
  *Gaussian process models for the sphere with application to the rotation measures of the near galactic sky*

**Monday, June 5th**

**17h00-18h40**: Session 5. *Applications*

*Chair:* **Mostert, Paul** (Universiteit Stellenbosch, South Africa)

- **Higdon, D.*** (Los Alamos National Lab., USA) [dhigdon at lanl.gov]
  **Habiib, S.** (Los Alamos National Laboratory, USA)
  **Heitmann, K.** (Los Alamos National Laboratory, USA)
  **Nakhleh, C.** (Los Alamos National Laboratory, USA)
  *Estimating Cosmological parameters using physical observations and simulations*

- **Haslett, J.** (Trinity College Dublin, Ireland)
  **Gelfand, A.** (Duke University, USA)
  **Huntley, B.** (University of Durham, UK)
  **Wilson, S.*** (Trinity College Dublin, Ireland)
  **Salter-Townshend, M.** (Trinity College Dublin, Ireland)
  **Parnell, A.*** (Trinity College Dublin, Ireland) [parnella at tcd.ie]
  *Bayesian palaeoclimate reconstruction*

- **Kennedy, M.** (University of Sheffield, UK)
  **O'Hagan, A.*** (University of Sheffield, UK) [a.ohagan at sheffield.ac.uk]
  **Anderson, C.** (University of Sheffield, UK)
  **Lomas, M.** (University of Sheffield, UK)
  **Woodward, I.** (University of Sheffield, UK)
  **Heinemeyer, A.** (University of York, UK)

*Quantifying uncertainty in the biospheric carbon flux for England and Wales*

- **Figini, S.*** (Università di Pavia, Italy) [silvia.figini at phd.uni-bocconi.it]
  **Giudici, P.** (Università di Pavia, Italy)
  **Brooks, S.** (Cambridge University, UK)
  *Bayesian feature selection to estimate customer survival*

**19h10-20h50**: Session 6. *Modelling*

*Chair:* **Steel, Mark** (University of Warwick, UK)

- **Green, P.J.*** (University of Bristol, UK) [P.J.Green at bristol.ac.uk]
  **Mardia, K. V.** (University of Leeds, UK) [sta6kvm at maths.leeds.ac.uk]
  **Ruffieux, Y.** (University of Bristol, UK) [yann.ruffieux at epfl.ch]
  *Bayesian matching and alignment*

- **Blei, D. M.*** (Princeton University, USA) [blei at cs.cmu.edu]
  **Lafferty, J. D.** (Carnegie-Mellon University, USA)
  *Modelling the evolution of Science*

- **Airoldi, E. M.*** (Carnegie-Mellon Univ., USA) [eairoldi+ at cs.cmu.edu]
  **Blei, D. M.** (Princeton University, USA)
  **Fienberg, S. E.** (Carnegie-Mellon University, USA)
  **Xing, E. P.** (Carnegie-Mellon University, USA)
  *Latent mixed-membership allocation models of relational and multivariate attribute data*

- **Smith, J. Q.*** (University of Warwick, UK) [j.q.smith at warwick.ac.uk]
  **Anderson, P. E.** (University of Warwick, UK)
  *Bayesian representations using chain event graphs*

**Tuesday, June 6th**

**17h00-18h40**: Session 7. *Model selection and comparison*

*Chair:* **Lee, Herbert** (University of California at Santa Cruz, USA)

- **Hu, J.*** (MD Anderson Cancer Center, USA) [JHu at mdanderson.org]
  **Johnson, V.** (MD Anderson Cancer Center, USA)
  *Bayesian model selection using test statistics*

- **Goldstein, M.*** (Durham University, UK) [Michael.Goldstein at durham.ac.uk]
  **Wooff, D. A.** (Durham University, UK) [d.a.wooff at durham.ac.uk]
  *Bayesian model comparison: a geometric, graphical approach*

- **Draper, D. *** (University of California at Santa Cruz, USA) [draper at soe.ucsc.edu]
  **Krnjajic, M.** (University of California at Santa Cruz, USA)
  *Bayesian model specification*

- **Pericchi, L. R.** (Universidad de Puerto Rico, USA) [lrpericchi at uprrp.edu]
  *Objective Bayesian testing of classical tests*

**19h10-20h50**: Session 8. *Theory*

*Chair:* **Rousseau, Judith** (Université de Paris Dauphine and CREST, France)

- **Spitzner, D.** (Virginia Tech., USA) [dspitzne at vt.edu]
  *An asymptotic viewpoint on high-dimensional Bayesian testing*

- **Bernardo, J. M.*** (Universitat de València, Spain) [jose.m.bernardo at uv.es]
  **Pérez, S.** (Colegio de Postgraduados, Mexico) [sergiop at colpos.mx]
  *Comparing normal means: New methods for an old problem*

- **Fraser, D. A. S.*** (University of Toronto, Canada) [dfraser at utstat.utoronto.ca]
  **Reid, N.** (University of Toronto, Canada)
  **Marras, E.** (Università di Roma La Sapienza, Italy)
  **Yi, G. Y.** (Univ. of Waterloo, Canada)
  *Two new procedures for developing model-based priors for default Bayesian analysis*

- **Grunwald, P. D.** (CWI Amsterdam, Netherlands) [Peter.Grunwald at cwi.nl]

*Bayesian inconsistency under misspecification* ▮

## Financial Statement

(Up to May, 2006)

(Tentative)

**Balance Amount:**

A. (brought forward from previous year):
26708.00+2540.00 (rounded from 2539.35)
= Rs. 29248.00

B. **Membership amount** (up to 12.5.06)
= Rs. 5190.00

C. Interest paid: = Rs. 986.00

**D. Total (A+B+C): = Rs. 35424.00**

**Expenditure:**

Typing of vol. II(2), Nov. 2005 = Rs. 240.00
Photostat charges: = Rs.. 417.00
Postage: = Rs. 624.00
Preparation of audited statement: = Rs. 500.00
Other expenses: = Rs. 100.50

E. Total: = Rs. 1881.50

F. Bank Clearance: = Rs. 94.00

**Balance available (D-E-F):**

**= Rs. 33448.50**

Edited by: S.K. Upadhyay & U. Singh, Department of Statistics, Banaras Hindu University, Varanasi- 221005, INDIA

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