SEPTEMBER 2025
VOL. 32 NO. 3

INTERNATIONAL SOCIETY FOR BAYESIAN ANALYSIS

THE ISBA BULLETIN

OFFICIAL BULLETIN OF THE INTERNATIONAL SOCIETY FOR BAYESIAN ANALYSIS

MESSAGE FROM THE PRESIDENT

Michele Guindani
president@bayesian.org

IN THIS ISSUE

FROM THE EDITOR

Francesco Denti
francesco.denti@unipd.it

FROM THE PROGRAM COUNCIL

Sameer Deshpande
program-council@bayesian.org

ISBA 2026 World Meeting

The 2026 ISBA World Meeting is getting closer. We are very excited to see you in Nagoya, Japan, from June 28 to July 3, 2026!

Invited Sessions. The Scientific Committee received an overwhelming number of high-quality proposals for invited sessions, nearly double the total number of available slots in the program! Decision emails were sent to session organizers in mid-September. Thanks to everyone who submitted a session. If your session was not selected, please submit a proposal to give a contributed talk or poster (see below).

Contributed Talks & Posters. The Scientific Committee welcomes proposals for contributed talks and posters. Contributed talks will be around 15 minutes long. Please submit proposals using this form. Proposals received before 11:59pm (Anywhere on Earth) on **November 21, 2025** will be considered for inclusion in the program as a contributed talk or a poster. Decisions will be announced in mid-December 2025. Proposals received after November 21, 2025, will be considered for inclusion in the program as a poster on a rolling basis, subject to space availability.

Please note that **one-oral-presentation-per-person policy** is in effect for the meeting: Each participant can give at most **one** oral presentation. All talks (invited or contributed), discussions, panel discussions, and poster presentations count as oral presentations. Limited exceptions to this policy may be made at the discretion of the Program Council to accommodate program needs.

Short Course. If you are interested in teaching a half-day (i.e., 3-hour) short course at the 2026 ISBA World Meeting, please email the Program Council at program-council@bayesian.org The Short Course is scheduled to run from 10am to 1pm on **Sunday, June 28, 2026**.

Plenary Speakers. The 2026 ISBA World Meeting will feature four Foundational and four Keynote Lectures. Foundational Lectures celebrate excellent researchers who have made notable and substantial contributions to the Bayesian community throughout their careers. Keynote Lectures highlight exciting new research developments.

The Scientific Committee is delighted to announce that David Dunson, Hal Stern, Sylvia Richardson, and Siddhartha Chib will deliver the Foundational Lectures and that Fumiyasu Komaki, Botond Szabo, Barbara Engelhardt, and Emtiyaz Khan will deliver the Keynote Lectures.

Local travel & registration information. The Local Organizing Committee has posted some local information — including directions to Nagoya and to the venue, a list of accommodation options, and some local attractions — on the meeting website. Registration rates will be posted on the meeting website in mid-October 2025, and registration will open in early 2026.

Endorsement Requests

If you are planning a meeting and would like to request financial (co-)sponsorship or non-financial endorsement from ISBA, please submit your request to the Program Council. Detailed information on how to submit such requests is available at this link

UPDATES FROM BA

Igor Prünster
igor@unibocconi.it

Editorial Updates

The first nine months of 2025 have seen a substantial increase in submissions to *Bayesian Analysis*, up by about 25% compared to the same period last year. This growth reflects the vitality of our field and the active engagement of the community with the journal as a venue for high-quality Bayesian research. At the current pace, we are on track to well over 300 submissions by the end of the year.

You will also notice that the September 2025 issue of *Bayesian Analysis* is somewhat "thicker" than usual. This reflects our decision to reduce the backlog in the Advance Publication section. While papers published there are final and assigned a DOI, the queue had grown to about 1.5 years, which we felt was too long. To address this, we are increasing the number of articles in each issue until we reach a more balanced equilibrium.

Last but not least, I am very pleased to report that we have met the goals we set ourselves earlier this year in terms of turnaround times and, in particular, in controlling outliers. All papers submitted within the first five months of 2025 have already received a decision, meaning within four months of submission. I want to sincerely thank our Co-Editors, Associate Editors, and referees for their diligence and responsiveness — and for their patience when I chase them for updates. The credit for this achievement is entirely theirs. We will continue to do our best to sustain this momentum, as a timely and consistent editorial process is crucial to attracting the community's best work. I very much hope this will further encourage researchers to consider *Bayesian Analysis* as the preferred outlet for their top-tier work.

Discussion Papers

In mid-September, we hosted the webinar for the discussion paper A Tree Perspective on Stick-Breaking Models in Covariate-Dependent Mixtures by A. Horiguchi, C. Chan, and L. Ma. The invited discussions by S. MacEachern, A. Rodriguez, D. Dahl, and G. Page, as well as those by B. Franzolini and G. Rebaudo, together with many stimulating contributed discussions, provided a rich set of complementary perspectives, ranging from theoretical insights into covariate-dependent nonparametric models to practical considerations for computation and applications. I am grateful to the authors, discussants, and all participants for making this a great success.

We now look forward to the webinar for our next discussion paper, Model Uncertainty and Missing Data: An Objective Bayesian Perspective by G. García-Donato, M.E. Castellanos, S. Cabras, A. Quirós, and A. Forte. It will take place on *November 5, 2025, at 4:00pm UTC*, with invited discussions by M. Clyde, M. Ferreira, A. Ly, and J. Rubio. I warmly encourage you to join us.

Online Resources

I would like to sincerely thank Julyan Arbel and the whole ISBA Media Team for the outstanding work they are doing behind the scenes to ensure the smooth running of the webinars. In addition, they have created a dedicated webpage gathering all BA webinars since 2019:

https://bayesian.org/ba-webinars/

This page brings together a remarkable collection of talks that span the full breadth of Bayesian statistics.

Beyond the webinars, the team has also reorganized the ISBA YouTube channel, which now features curated playlists from ISBA World Meetings (2012–2024), specialized workshops and seminars, and content from ISBA Sections (j-ISBA, BNP, BioPharma, Industrial). These resources deserve broad visibility, and I encourage you to explore them, share them with colleagues and students, and provide feedback to Julyan (julyan.arbel@inria.fr).

AWARDS

Surya Tokdar and Lucia Paci
prize-committee@bayesian.org

Savage Applied Methodology 2024

Awards Committee:
Veronica Berrocal (Chair; UC Irvine, USA); Roberta De Vito (Brown University, USA); Dani Gamerman (UFRJ, Brazil); Clara Grazian (University of Sydney, Australia); Andrew Holbrook (UCLA, USA); Juhee Lee (UC Santa Cruz, USA); Andrew Zammit-Mangion (University of Wollogong, Australia).

Honorable Mentions:
Nicholas Marco, PhD at UCLA; *"Mixed Membership Models with Applications to Neuroimaging."*
Melodie Monod, PhD at Imperial College London; *"Bayesian Models and Methods to Estimate Age-specific Infectious Disease Transmission Dynamics."*

Winner:
Alessandro Zito, PhD at Duke University; *"Ecological Modeling via Bayesian Nonparametric Species Sampling Priors."*

Savage Theory and Methods 2024

Awards Committee:
Marta Catalano (Luiss University); Peter Hoff (Duke University); Jaeyong Lee (Chair; Seoul National University); Kyungjae Lee (Sungkyunkwan University); Feng Liang (University of Illinois Urbana–Champaign); Depdeep Pati (University of Wisconsin); Yanxun Xu (Johns Hopkins University).

Honorable Mention:
Maria Gil-Leyva, PhD at National Autonomous University of Mexico; *"Stick-breaking Processes and Related Random Probability Measures."*

Winner:
Takuo Matsubara, PhD at Newcastle University; *"Bridging the Gap Between Modeling and Computation in Bayesian Statistics."*

Mitchell Prize 2024

Awards Committee:
Chris Drovandi (Queensland University of Technology, Australia); Didong Li (University of North Carolina, USA); Finn Lindgren (University of Edinburgh, UK); Brian Reich (Chair; North Carolina State University, USA); Toryn Schafer (Texas A&M University, USA).

Honorable Mentions:

- Ethan M. Alt, Xiuya Chang, Xun Jiang, Qing Liu, May Mo, Hong Amy Xia, and Joseph G. Ibrahim (2024). LEAP: The Latent Exchangeability Prior for Borrowing Information from Historical Data. *Biometrics*, 80(3): 1–10.
- Georgia Papadogeorgou, Carolina Bello, Otso Ovaskainen, and David B. Dunson (2023). Covariate-Informed Latent Interaction Models: Addressing Geographic & Taxonomic Bias in Predicting Bird–Plant Interactions. *Journal of the American Statistical Association*, 118(544): 2250–2261.

Winner:
Clara Hoffmann and Nadja Klein (2023). Marginally Calibrated Response Distributions for End-to-End Learning in Autonomous Driving. *Annals of Applied Statistics*, 17(2): 1740–1763.

JUNIOR ISBA

Matteo Giordano
jisba.section@gmail.com

Dear ISBA community,
On behalf of the j-ISBA Board, let me say that it was wonderful to meet so many of you at the social event we organized during the BNP in Los Angeles, where more than 100 of you attended!

Looking forward, we're excited to share updates on upcoming events and opportunities that continue to unite our early-career researchers' community, such as the upcoming BAYSM 2026, the next organized sessions, the peer mentoring scheme by j-ISBA, and the upcoming elections.

For any questions or suggestions, please feel free to reach out to the j-ISBA board via email at this email address, or also on our new official LinkedIn page.

Upcoming events

- The 2025 edition of the Blackwell-Rosenbluth Award is well underway. We look forward to announcing the winners soon!
- The next edition of BAYSM will be held on June 26 – 27, 2026, at Chiba University, Japan! This will be just before the ISBA World Meeting 2026. The planning for the event is in full swing, so stay tuned for more information!

- The ISBA Elections are coming, and we would greatly appreciate your vote! Please make sure to cast your ballot for the three opening positions on the j-ISBA board: Chair-Elect, Program Chair, and Secretary.
- Do not miss the next conference sessions organized by j-ISBA:
  - IDWSDS 2025 - International Day of Women in Statistics and Data Science Conference
    Date and location: October 14, 2025, Online
    This is a fully online and free event! j-ISBA is sponsoring the session "Advances from Junior Bayesian Statisticians" with the following amazing speakers: Beatrice Franzolini (Bocconi University), Yunshan Duan (Johns Hopkins University), and Daria Bystrova (Pierre Louis Institute of Epidemiology and Public Health). Find more info at https://www.idwsds.org/.
  - CFE-CMStatistics Computational and Methodological Statistics Conference
    Date and location: December 13-15, 2025, London
    j-ISBA is sponsoring the session "j-ISBA session on new advances in Bayesian statistics" where you can hear about the interesting work of Myung Won Lee (University of Edinburgh), Harita Dellaporta (University College London), Luke Hardcastle (University College London) and Gerardo Duran-Martin (University of Oxford).

Peer mentoring

The j-ISBA Peer Mentoring Scheme is an opportunity for you to be paired online with another young researcher in the field, providing a friendly and secure place to seek support and guidance. Peer mentors are j-ISBA members who have volunteered to join the program. Based on their experiences, they will be able to offer you advice on how to navigate the uncertainties and difficulties that may arise during your early years in research.

j-ISBA is currently seeking Peer Mentors for the academic year 2025-26. If you are interested in supporting our community of young Bayesian statisticians in this way, please get in touch by email with the j-ISBA board.

SOFTWARE HIGHLIGHT

Luca Porta Mana
Western Norway University of Applied Sciences
pgl@portamana.org

inferno: INFERence in R with Bayesian NOnparametrics

Population inference and Bayesian nonparametrics

A very important kind of inference in research fields such as medicine is *population inference*, also called "density inference" or "density regression". Its general goal is to infer the frequency distribution of some variates in a population. This is different, for instance, from *functional regression*, where the goal is to infer the functional relationship – assumed to exist – between a set of predictor variates and a target or "predictand" variate. In population inference the existence of a functional relation cannot be assumed. In fact there may not even be a clear distinction between predictor and predictand variates. A typical goal is the inference of frequency distributions within particular sub-populations or sub-groups; thus all sorts of conditional probabilities are required. A clinician may be interested in the statistics and probability of a medical condition given a symptom, but also in

perhaps: many conditional probabilities may be of interest.

perhaps: certain statistics and probabilities

that of a symptom given a medical condition; and maybe only within subjects of a given sex or age. De Finetti's theorem (see e.g. Bernardo and Smith, 2000, §§ 4.2, 4.3, 4.6) lies at the heart of population-inference methods; a particularly brilliant discussion is given by Lindley & Novick (1981).

h i s
eems a
it strong.

erhaps:
lowever

Sadly many researchers still approach population-inference problems by means of p-values or other frequentist practices, which only give limited, coarse, and not seldom misleading results about a population's frequency distribution. Some researchers adopt Bayesian methods but limit themselves to *parametric* ones, which make very restrictive and possibly unrealistic assumptions about the population's distribution; as opposed to *nonparametric* ones, which do not.

Until a couple decades ago the use of parametric methods, and maybe even of frequentist practices, had pragmatic reasons. Better methods were computationally too costly or unfeasible. Population-inference problems were low-dimensional; one could *visually* check whether the assumptions were appropriate and the results reasonable. But today these reasons cannot earnestly be given (Walker, 2010). Bayesian nonparametric methods have become computationally feasible for many kinds of inference. Many inference problems today involve from tens to thousands of variates; it is impossible to visually check in such high-dimensional spaces whether frequentist practices or parametric assumptions are acceptable, or by how much they err. Results may be affected by large parametric-modelling errors (Draper, 1995).

erhaps:
s e
ayesian
onparamet
ic analyses

But there is still one reason today for why Bayesian nonparametric methods are avoided: *lack of user-friendly software*. Many clinical researchers might like to try a Bayesian nonparametric analysis, but cannot: they would need to study Markov-chain Monte Carlo (MCMC) techniques, programming languages to implement the latter, and a read about plethora of debated practices to "assess convergence". Most clinicians do not have time to learn all this even if they wanted to. Also, available packages for Bayesian nonparametrics are not quite suited to population inference. Some of them focus on functional regression, which as discussed above is not an appropriate assumption. Some make a priori distinctions between predictor and predictand variates, limiting the range of useful inferences. Most still require MCMC programming expertise.

The R-package **inferno**[1] was built to try to remedy the lack of user-friendly software of this kind.

Use and features

Using the package is simple. The user first provides a data sample S of variates from a population, for instance age, sex, symptom, disease, and kind of treatment of a number of patients that satisfy specific criteria. The package can work with any combination of continuous, discrete ordinal, nominal, and binary variates. Continuous variates can be defined in bounded intervals, and can also have boundary values with finite probability mass, as it may happen with censoring. The package cannot handle periodic variates yet, or variates with complex topology, such as images. The data sample and the variate characteristics (type, domain, possible censoring) are provided by the user as two CSV files to an R function called `learn()`.

The package then runs a MCMC computation by means of the **Nimble** package[2], using parallel CPUs if available, to find the probability distribution over all possible joint frequency distributions of the variates. The result is saved in an R object called `learnt`. The crucial point here is that this computation is automatic and does not require any further control from the user, who is simply informed at regular intervals about the expected end time of the computation. (Optional arguments still allow users expert in MCMC to control many parameters such as number of chains, target effective sample size, thinning and burn-in, and even some hyperprior parameters.)

Once the computation has finished, the user can inquire multiple times about any of the following:

- For a new unit of the population, say a new patient, the conditional probability (density) for the

[1] https://pglpm.github.io/inferno/
[2] https://r-nimble.org/

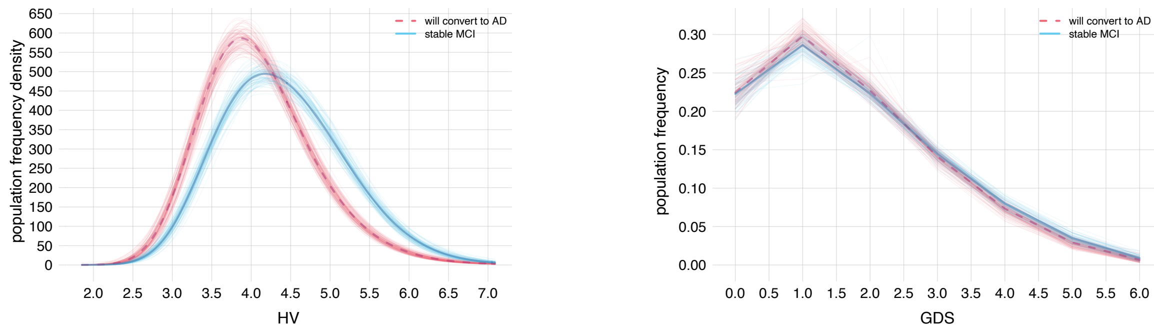

Figure 1

Define `S` here

values of *any* set of variates $A{=}a, B{=}b, \dots$ given *any* other set $C{=}c, D{=}d, \dots$:

$$\mathrm{P}(A{=}a, B{=}b, \dots \mid C{=}c, D{=}d, \dots, S) \tag{1}$$

Such a probability could for instance be used in medical decision making (Sox et al., 2024; Hunink et al., 2014). The conditional can be empty; tail probabilities (e.g. $A \geq a$, $C \leq c$) can also be requested.

- The probability distribution for the conditional *frequencies*, in the whole unsampled population, of the values of any set of variates given any other set (possibly empty). If we denote the frequency distribution by F and a specific value by f, this probability can be written

more detail or citation - is this MacKay?

$$\mathrm{P}\big[F(A{=}a, \dots \mid C{=}c, \dots) = f \bigm| S\big]\, \mathrm{d}f \,. \tag{2}$$

This probability distribution is represented by the MCMC samples f_i drawn from it by `learn()`.

- The mutual information (MacKay, 2005, Ch. 8) between any two sets of quantities.

Probabilities (1) and (2) are connected by a variant of de Finetti's theorem:

$$\mathrm{P}(A{=}a, \dots \mid C{=}c, \dots, S) = \int f\, \mathrm{P}\big[F(A{=}a, \dots \mid C{=}c, \dots) = f \bigm| S\big]\, \mathrm{d}f \,. \tag{3}$$

Overall - more modeling details are needed - then discuss the conditioning - what is being passeed to Nimbl

In a manner of speaking, the probability distribution (2) expresses how much the probability value (1) could change, if it were updated by sampling the whole population. It expresses the uncertainty in the statistical results owing to finite sample size.

The package function `Pr(Y, X, learnt)` does the first two kinds of calculations. The user provides a list `Y` of predictand variates and values of interest; an optional, analogous list `X` of predictors; and the `learnt` object produced by `learn()`. The calculation of mutual information is done by the package function `mutualinfo(Y1names, Y2names, X)`, where the first two arguments are the variate sets of interest, and the optional third argument is a set of variate values to conditionalize upon.

I haven't heard this term before

The package allows the user to visualize the probabilities above when just one predictand and one predictor variates are involved. If the results of the `Pr()` function are saved in some object, say `probs`, then the visualization is done by simply calling `plot(probs)`.

Figure 1 shows two examples from a study (Porta Mana et al., 2023) about conversion from Mild Cognitive Impairment (MCI) to Alzheimer's Disease (AD); they can be used to further illustrate the probability distributions (1) and (2).

In the plot on the left, the predictand variate is Hippocampal Volume (HV); the predictor is the yes/no variate 'will convert to AD' (cAD). The thick solid blue line and thick dashed red line are the

Posterior median and sample draws? I don't really see the red.

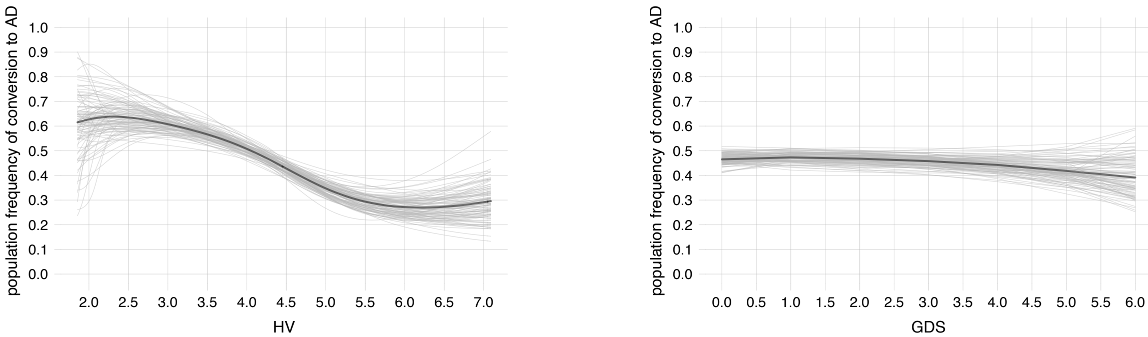

Figure 2

I am not sure what you mean

conditional probability distributions (omitting the sample-data dependence)

$$\mathrm{P}(HV \mid cAD{=}\mathrm{N}) , \qquad \mathrm{P}(HV \mid cAD{=}\mathrm{Y}) .$$

The cloud of thinner blue lines surrounding the first distribution above represents the probability distribution

$$\mathrm{P}\big[F(HV \mid cAD{=}\mathrm{N})\big]$$

Maybe a fuller discussion of going from the MCMC sample to the conditional probability will help the reader

of possible frequency distributions; each thin line is a sample from this distribution.

Looking at this plot, a clinician can immediately see that the frequency distributions of hippocampal volume in the sub-populations of patients that will convert to Alzheimer's, and in those who will not, are different. Such a difference is almost certain even accounting for the uncertainty from the finite sample size. The plot on the right is analogous but for the predictand variate 'Geriatric Depression Scale' (GDS) in stead of hippocampal volume. In this case the clinician sees that the frequency distributions for the two sub-populations cannot be distinguished within the finite-sample uncertainty.

It is exactly this kind of differences and uncertainties that clinical researchers often try to clumsily capture through p-values. In private communications, several clinical researchers expressed elation at the capacity to visualize the estimates of different sub-population statistics, and even more the uncertainties they carry because of finite sample size.

As you have the posterior wouldn't a quantile be a credible interval?

The quick analysis above is mostly qualitative, but concrete numbers, such as quantiles and credibility intervals, expected values, and so on, can be easily produced. This becomes necessary when many variates are considered jointly and visualization is impossible. In such high-dimensional cases the package allows the user to compute the credibility intervals for any kind of distance between two frequency distributions (e.g. Hellinger or Kantorovich or Shannon-Jansen distance, or relative entropy). The computation of the mutual information between any two sets of variates, illustrated in a vignette[3], gives moreover a measure of their association that does not depend on assumptions such as linearity or gaussianity.

Perhaps more detail here

The ability to swap the "predictor" and "predictand" roles of any variates is illustrated in the plots of fig. 2, parallel to those of fig. 1. In the left plot, the thicker lines show the probabilities

$$\mathrm{P}(cAD{=}\mathrm{Y} \mid HV)$$

for various values of the HV variate, which is now a predictor. We see for example that among individuals having hippocampal volume around 5.0, between 30% and 40% will convert to Alzheimer's. Among those with volume around 2.0, we can only say that between roughly 45% and 80% will

[3] https://pglpm.github.io/inferno/articles/mutualinfo.html

convert; in this case the finite-sample size (few samples with this HV value) leads to a much larger uncertainty of the frequency estimates.

The possibility of swapping predictor and predictand roles makes it also possible to implement, on the fly, corrections for base rates by means of Bayes's theorem (Lindley and Novick, 1981, § 4).

Plots and calculations like the ones above are of course nothing new in Bayesian nonparametrics. The point here is that the user can produce them just by inputting the population sample in the package, waiting for the MCMC computation to finish, and then simply asking about variates of interest and plotting the results. The sequence of commands could be as simple as

```
learnt <- learn(data = 'data.csv', metadata = 'metadata.csv')
## Information about MCMC and expected end time...

probs <- Pr(Y = list(A = seq(0, 8, 0.1)), X = list(C = c('yes', 'no')), learnt)

plot(probs)
```

More extensive use examples are given in the package's main vignette[4]. The package has also been used to "calibrate" the output of machine-learning algorithms (Dyrland et al., 2022), improving their performance. Readers of the ISBA Bulletin are probably interested in the internals of the package, discussed next.

Internals

In nonparametric population inference the prior and posterior probability distributions are over an in-principle infinite-dimensional manifold of frequency distributions. The mathematical representation of this manifold is therefore crucial. The **inferno** package uses the ingenious representation of a distribution as a mixture of product kernels discussed by Dunson & Bhattacharya 2011. For example, a generic frequency distribution for variates A and B is written as

I think this material needs to be moved up - and then discuss the conditioning mathematics you have abov

$$F(A, B) = \sum_i w_i \, K_A(A \,|\, \alpha_i) \, K_B(B \,|\, \beta_i) \tag{4}$$

where w_i are normalized weights, K_A a distribution for variate A depending on parameters α_i, and similarly for K_B. The product is easily generalized to any number of variates. In principle the sum should be countably infinite, but as discussed in Ishwaran & Zarepour 2002 it is possible to truncate it if an appropriate Dirichlet distribution is used for the weights w_i. Thus a frequency distribution F is effectively represented, non-uniquely, by a very large but finite set of parameters (w_i, α_i, β_i).

The representation above was somewhat deprecated in recent works which, however, consider inference problems where variates have clear predictor or predictand roles (e.g. Wade et al., 2014b,a). As previously discussed, in many research fields there are no such a-priori roles; any variate could assume both. A representation that can easily swap the two roles without overemphasizing either is therefore most appropriate. The representation (4) leads to very simple, symmetric, analytical expressions for the conditional of A given B and vice versa, and for any marginal:

$$F(A \,|\, B) = \sum_i \frac{w_i \, K_A(A \,|\, \alpha_i) \, K_B(B \,|\, \beta_i)}{\sum_j w_j K_B(B \,|\, \beta_j)} \qquad F(B \,|\, A) = \sum_i \frac{w_i \, K_B(B \,|\, \beta_i) \, K_A(A \,|\, \alpha_i)}{\sum_j w_j K_A(A \,|\, \alpha_j)}$$

$$F(A) = \sum_i w_i \, K_A(A \,|\, \alpha_i) \, .$$

[4] https://pglpm.github.io/inferno/articles/inferno_start.html

Discuss the full mo

The (hyper)prior over the parameters representing the frequency distribution is a Dirichlet-process mixture. It allows for distributions having multiple, possibly sharp, peaks. For information about the kernels K for different kinds of variates, and about the prior distribution, see the technical manual[5].

The MCMC computation is based on Gibbs sampling; several chains are run in parallel. The stopping rule implements variations of the methods discussed in Vehtari et al. (2021). Regarding MCMC sampling, the package takes the following stance:

• For this kind of inference problems there is no need for tens of thousands or more independent MCMC samples (effective sample size). The package's default is just 3600. The mean of such samples is the probability (1), and the numerical uncertainty in this mean is thus around $\sqrt{3600} = 60$ times smaller than the "variability" of this probability, given by eq. (2).

• It is acceptable that the sampling has not *fully* converged (emphasis on 'fully'). Why? Consider that machine-learning algorithms such as neural networks are effectively Bayesian nonparametric functional regressors, and their training is essentially an *unconverged* Monte Carlo sampling (see e.g. MacKay, 1992; Gal, 2016; Mandt et al., 2017; Huszár, 2017). This "sampling" stops at a *local* maximum of the posterior, and all samples are discarded. Thanks to this lack of convergence, neural-network training is fast; despite this lack of convergence, inferences can still be impressive. It is this writer's opinion that the same stance can and should at times be adopted in Bayesian nonparametrics: inferences can still be impressive and informative despite lack of full MCMC convergence, and superior to those of many machine-learning algorithms designed for the same task, as we found by using this package. And the uncertainty in the results can moreover be approximately assessed, instead of fully discarded as in neural-network training. So far, in applying **inferno** to concrete problems, we noticed that the MCMC sampling had converged in the majority of cases. In those in which it had not fully converged, the results were still correct to a good approximation, for example with credibility intervals that erred by less than 2% from the converged values. This kind of approximate nonparametric results are still vastly superior to precise but opaque p-values.

Perhaps: Due to this

I am sti havin some issu here - as it hasn' converge then it i not in th space o t h posterio Do yo m e a mixing o the MCMC'

These stances are motivated by the need for user-friendliness. The ultimate goal of the package is to let frequentist practitioners try and appreciate Bayesian methods (the package's main vignette is specially written for them); to let Bayesian-parametric practitioners try nonparametrics; and to show that Bayesian methods can be almost as fast and more powerful than many machine-learning approaches. Once the merits are seen, practitioners can slowly move to more complex Bayesian packages that allow for more control and custom problem-solving.

inferno has been already used and tested in several studies, but we'd like more testing before submitting it to CRAN. Testers and feedback are very welcome!

References

J.-M. Bernardo and A. F. Smith. *Bayesian Theory*. Wiley series in probability and mathematical statistics. Wiley, New York, repr. edition, 2000. doi:10.1002/9780470316870. First publ. 1994.

J. M. Bernardo, M. J. Bayarri, J. O. Berger, A. P. Dawid, D. Heckerman, A. F. M. Smith, and M. West, editors. *Bayesian Statistics 9*. Oxford University Press, Oxford, 2011. doi:10.1093/acprof:oso/9780199694587.001.0001.

D. Draper. Assessment and propagation of model uncertainty. *J. R. Stat. Soc. B*, 57(1):45–70, 1995. doi:10.1111/j.2517-6161.1995.tb02015.x. See also discussion and reply in Spiegelhalter et al. (1995).

D. B. Dunson and A. Bhattacharya. Nonparametric Bayes regression and classification through mixtures of product kernels. In Bernardo et al. (2011), pages 145–158. 2011. doi:10.1093/acprof:oso/9780199694587.003.0005.

K. Dyrland, A. S. Lundervold, and P. G. L. Porta Mana. Don't guess what's true: choose what's optimal. A probability transducer for machine-learning classifiers, 2022. Open Science Framework doi:10.31219/osf.io/vct9y, arXiv doi:10.48550/arXiv.2302.10578.

[5] https://github.com/pglpm/inferno/raw/main/development/manual/optimal_predictor_machine.pdf

Y. Gal. *Uncertainty in Deep Learning*. PhD thesis, University of Cambridge, Cambridge, 2016. https://www.cs.ox.ac.uk/people/yarin.gal/website/thesis/thesis.pdf.

N. L. Hjort, C. Holmes, et al., editors. *Bayesian Nonparametrics*. Cambridge series in statistical and probabilistic mathematics. Cambridge University Press, Cambridge, 2010. doi:10.1017/CBO9780511802478.

M. G. M. Hunink, M. C. Weinstein, et al. *Decision Making in Health and Medicine: Integrating Evidence and Values*. Cambridge University Press, Cambridge, 2 edition, 2014. doi:10.1017/CBO9781139506779. First publ. 2001.

F. Huszár. Everything that works works because it's Bayesian: Why deep nets generalize?, 2017. http://www.inference.vc/everything-that-works-works-because-its-bayesian-2.

H. Ishwaran and M. Zarepour. Exact and approximate sum representations for the Dirichlet process. *Can. J. Stat.*, 30(2):269–283, 2002. doi:10.2307/3315951.

D. V. Lindley and M. R. Novick. The role of exchangeability in inference. *Ann. Stat.*, 9(1):45–58, 1981. doi:10.1214/aos/1176345331.

D. J. C. MacKay. A practical Bayesian framework for backpropagation networks. *Neural Comput.*, 4(3):448–472, 1992. https://www.inference.org.uk/mackay/PhD.html, doi:10.1162/neco.1992.4.3.448.

D. J. C. MacKay. *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, Cambridge, version 7.2 (4th pr.) edition, 2005. https://www.inference.org.uk/itila/book.html. First publ. 1995. See also video lectures at https://videolectures.net/events/course_information_theory_pattern_recognition.

S. Mandt, M. D. Hoffman, and D. M. Blei. Stochastic gradient descent as approximate Bayesian inference. *J. Mach. Learn. Res.*, 18:134, 2017. https://www.jmlr.org/papers/v18/17-214.html.

P. G. L. Porta Mana, I. Rye, et al. Personalized prognosis & treatment using an optimal predictor machine: An example study on conversion from mild cognitive impairment to Alzheimer's disease, 2023. Open Science Framework doi:10.31219/osf.io/8nr56.

H. C. Sox, M. C. Higgins, et al. *Medical Decision Making*. Wiley, New York, 3 edition, 2024. doi:10.1002/9781119627876. First publ. 1988.

D. J. Spiegelhalter, A. P. Grieve, et al. Discussion of the paper by Draper. *J. R. Stat. Soc. B*, 57(1):71–97, 1995. doi:10.1111/j.2517-6161.1995.tb02016.x. See Draper (1995).

A. Vehtari, A. Gelman, et al. Rank-normalization, folding, and localization: An improved $\hat{R}$ for assessing convergence of MCMC. *Bayesian Anal.*, 16(2):667–718, 2021. doi:10.1214/20-BA1221. With invited discussion.

S. Wade, D. B. Dunson, et al. Improving prediction from Dirichlet process mixtures via enrichment. *J. Mach. Learn. Res.*, 15(30):1041–1071, 2014a. http://jmlr.org/papers/v15/wade14a.html.

S. Wade, S. G. Walker, and S. Petrone. A predictive study of Dirichlet process mixture models for curve fitting. *Scand. J. Stat.*, 41(3):580–605, 2014b. doi:10.1111/sjos.12047.

S. G. Walker. Bayesian nonparametric methods: motivation and ideas. In Hjort et al. (2010), chapter 1, pages 22–34. 2010. doi:10.1017/CBO9780511802478.002.

NEWS FROM THE WORLD

Déborah Sulem
deborah.sulem@usi.ch

Reports from events and conferences

BayesComp 2025 @NUS, Singapore
by David Frazier

The biannual BayesComp conference was successfully held from June 16 to 20 at University Town, National University of Singapore. This year's conference marked the first time it was held in Asia, and the turnout was impressive, featuring over 250 participants from more than 25 different countries. The conference program featured over 30 invited and contributed sessions spanning a range of topics in Bayesian computation, with model misspecification and approximate Bayesian inference/computation being consistent themes present throughout the conference. In addition to the main conference, two fascinating satellite meetings were also held: "Bayesian Computation and Inference with Misspecified Models" and "Bayesian Methods for Distributional and Semiparametric Regression".

On behalf of the local organizer, David J. Nott, and my fellow scientific co-chair, Leah South, I would like to sincerely thank the local organizers, satellite organizers, scientific committee, and the participants themselves for making this year's conference a success. The next iteration of the conference will take place at Texas A&M in 2027.

European Seminar on Bayesian Econometrics 2025 @University of Melbourne, Australia
by Jamie Cross

The 2025 European Seminar on Bayesian Econometrics (ESOBE) was held at the University of Melbourne from August 25 to August 28. This year's edition was hosted in Australia for the first time, with support from the Faculty of Business and Economics and Melbourne Business School at the University of Melbourne, Monash University's Department of Econometrics and Business Statistics, and the Economics, Finance, and Business Section of ISBA.

Program Highlights The seminar was held on campus at the university's dedicated conference facility, which commanded 360-degree views over the city of Melbourne. The program featured a rich set of keynotes, invited talks, and contributed sessions.

Keynote lectures were delivered by Christiane Baumeister (University of Notre Dame) on a novel nonlinear heterogeneous agent VAR, Dimitris Korobilis (University of Glasgow) on quantile VAR modelling of oil markets, and Howard Bondell (University of Melbourne) on density ratio estimation.

Invited talks included presentations from Dan Zhu (Monash University) on a new functional approach for modelling inflation target at risk, and David Frazier (Monash University) on Generalized Bayesian Methods for Predictive Inference.

Contributed sessions by junior and established scholars showcased high-quality Bayesian papers. These spanned causal inference, time series models, generalized Bayes, micro- and macro-econometric applications, and new machine learning and other methodologies that aim to capture distributional dynamics.

A well-attended poster session featured new developments in variational inference, copula methods, clustering methods, frontier models, high-frequency time series, policy evaluation, and even F1 racing.

The meeting was complemented by two fantastic masterclasses on contemporary topics: Neural Methods for Amortised Inference, delivered by Andrew Zammit Mangion (University of Wollongong); and Advances in Bayesian Finite Mixture Modeling was taught by Bettina Grün (WU Vienna).

Honoring Herman K. van Dijk A special moment of this year's ESOBE was the inaugural Herman K. van Dijk seminar, given by Dimitris Korobilis. The seminar was established in memory of Herman, who was a pioneer in Bayesian econometrics and a founding figure behind ESOBE.

Community and Engagement The conference fostered a highly interactive environment, bringing together established leaders and emerging scholars. Social events included the conference dinner at University House in one of its historically decorated private rooms, and an excursion to the National Gallery of Victoria, which involved both a lunch overlooking the sculpture garden and a tour of its unique Australian art collection.

Sister Event After the conclusion of ESOBE, many of the participants travelled to a Bayesian macroeconometrics workshop held at the University of Queensland in the city of Brisbane. This two-day event was deliberately scheduled to follow on from the seminar in Melbourne and focused on a field where Bayesian thinking has become a popular choice for practitioners.

Conclusion ESOBE 2025 continued the tradition of advancing Bayesian econometric research in an open and collegial setting. The program highlighted both cutting-edge methodological innovations and substantive empirical applications, reinforcing the impactful role of Bayesian methods in economics, finance, and business.

SISBAYES 2025 Workshop @University of Padova, Italy

by Antonio Canale and Raffaele Argiento

The Department of Statistical Sciences at the University of Padova was the host for the second SISBAYES Workshop, organized by the Bayesian section of the Italian Statistical Society. The event brought together approximately 100 researchers from Italy and abroad for two days of stimulating scientific discussion and informal exchange of ideas.

The scientific program featured two foundational lectures by Sonia Petrone and Guido Consonni, alongside keynote addresses from Serena Arima and Tommaso Rigon. Six invited sessions were dedicated to modern topics in Bayesian analysis, including: Prior Elicitation for Complex Problems, Model-based Clustering, Bayesian Methods for Ecological Applications and Beyond, Bayesian Graphical Models, Bayesian Causal Inference, and Challenging Posteriors.

Reflecting a cherished ISBA tradition, a highlight of the workshop was the vibrant session for 40 contributed posters. It commenced with a welcome aperitif beneath the department's wisteria and extended into a moonlit evening, providing a distinctive and engaging atmosphere for discussion. The scientific committee presented awards to Matteo Gianella for developing a novel and suitable methodology for an applied problem, and to Laura Ferrini for her work on an innovative methodology accompanied by a thorough investigation of its theoretical properties. An honorable mention was awarded to Andrea Ongarato for developing an interesting methodology with promising applications.

The charming venue and welcoming atmosphere made the second SISBAYES Workshop both a delightful and productive experience for all attendees. The SISBayes board of directors is already looking forward to organizing the next event in 2027. Stay tuned!

BNP 14 @University of California, Los Angeles

by Alessandra Guglielmi and Michele Guindani

The BNP Section held its biannual international conference, BNP 14, from June 23 to 27, 2025, at UCLA in Los Angeles. The meeting drew approximately 300 participants, with particularly strong representation from the United States and Italy.

On June 22, the BNP 14 pre-conference program opened with a workshop titled "25 Years of Dependent Dirichlet Processes (DDP)". Introduced by MacEachern (1999–2000), the Dependent Dirichlet Process has, over the past quarter-century, inspired a rich literature on dependent random probability measures. This workshop honored that milestone by showcasing its theoretical advances, diverse applications, and future direction. A second satellite workshop on Bayesian Predictive Inference brought together researchers developing new approaches to predictive methods within Bayesian analysis, discussing both novel theory and implementation challenges.

The main scientific program of the conference featured three plenary speakers: Li Ma, Maria De Iorio, and Peter Müller, alongside five keynote lectures delivered by Federico Camerlenghi, Ismael Castillo, Stefano Favaro, Antonio Linero, and Sara Wade. The program also included 26 invited sessions (78 invited talks), 13 contributed sessions (52 contributed talks), and more than 90 poster presentations.

For the first time, keynote talks and invited sessions, in addition to contributed sessions, were held in parallel. The plenary and keynote talks provided insightful overviews of cutting-edge research. The invited and contributed sessions covered a wide range of topics, showcasing the latest developments in BNP. The poster sessions provided a lively forum for in-depth discussions. The social reception was a hit: we organized it as a private buffet light dinner in a restaurant with a bar, with ample time and space for social interaction among the participants. As one participant summarized it in their feedback, "the informal conference dinner helped socializing, and the presence of many PhD students made the atmosphere more lively and gave high hopes for the future of the community."

The BNP 14 scientific committee received more than 110 applications for junior travel awards, and approximately $38,000 in support was awarded to recipients from the United States, Canada, South Korea, and Europe. Sponsorship spanned multiple levels: Platinum sponsors were ERC Grant 817257 and Google DeepMind, and Silver-level supporters included the University of Texas at Austin (Department of Statistics & Data Sciences), Duke University (Department of Statistical Science), UCLA's Fielding School of Public Health (Department of Biostatistics) and College of Physical Sciences (Department of Statistics & Data Science), and Brigham Young University (Department of Statistics). One-third of the travel award funds were granted by the National Science Foundation to PhD students and postdoctoral researchers from US institutions. The meeting was co-sponsored by the Institute of Mathematical Statistics and endorsed by the ASA's Section on Bayesian Statistical Science, alongside ISBA.

The venue for BNP 15 will be finalized and announced soon.

Q&A: what do you ~~believe~~ think?

What does (Bayesian) statistical fairness mean to you?

Christos Dimitrakakis (University of Neuchatel)
There are many definitions of fairness, and each can be formalised in different ways. However, even with a given definition, whether or not something is fair can be subjective. There is also the question of what objects we are allowed to label as fair. There, I think the answer is unambiguous: it should be processes and policies rather than individual decisions or outcomes.

I personally would like to assign a degree of fairness to decision-making policies, given a certain amount of information: the same policy can be fair or unfair depending on the information given. Given the values of all latent variables, we can perfectly characterise the fairness of a policy. Otherwise, we can merely talk about fairness only in a distributional sense. This is something that is naturally captured in a probabilistic/Bayesian framework.

Francesca Panero (Sapienza University) *When browsing the literature on algorithmic fairness, one cannot help but notice how few Bayesian approaches are available. Why is that, one might ask? I would point to one main reason: fairness has mostly been approached from a machine learning and purely algorithmic perspective. In general, what is missing—and much needed—is a more statistical point of view, to better understand the theoretical characteristics of the constructed models.*

One clear contribution of Bayesian methods is the ability to investigate the impact of fair modeling choices (typically constraints on relations between sensitive variables and predictions) on model outputs and on the uncertainty of results. A field with such significant ethical, legal, and societal implications should indeed care more about these aspects.

Upcoming Meetings, Conferences, and Workshops

ISBA sponsored or endorsed events

- International Day of Women in Statistics and Data Science 2025, 14 October, online. This is a 24-hour-long free online conference. An ISBA-sponsored session features talks by Gemma Moran (Rutgers University), Cecilia Balocchi (University of Edinburgh), and Betsy Bersson (MIT).
- ISBA World Meeting 2026, June 28 - July 3, 2026, Nagoya, Japan. Deadline for contributed talks and posters: November 21.
- 4^{th} Bayesian Nonparametrics Networking Workshop, 6-10 July 2026, Seoul, South Korea. This meeting, organised by the Bayesian NonParametrics (BNP) Section, has a flexible schedule and dedicated slots for early-career researchers. It aims to enhance networking within the BNP community, particularly for junior researchers.

Other events

- Latin American Congress of Probability and Mathematical Statistics (XVII CLAPEM), 2-6 March

2026, Montevideo, Uruguay. This meeting is organised by the Latin American Society of Probability and Mathematical Statistics (SLAPEM) and the Latin American Regional Committee (LARC) of the Bernoulli Society. The deadline for submitting proposals for contributed sessions is November 10. Deadline for contributed talks and posters: December 10. Financial support is available (deadline for applications: November 30).

- Institute of Mathematical Statistics Annual Meeting 2026, 6-9 July 2026, Salzburg, Austria. This meeting will feature the 2026 Wald Lecture (Tilmann Gneiting), the 2026 Blackwell Lecture, three 2026 Medallion Lectures (Ian McKeague, Bodhisattva Sen, Jelle Goeman), and the IMS Lawrence D. Brown Ph.D.Student Awards, and more than 60 invited and contributed sessions. Deadline for invited session proposals: November 15, 2025.

And don't forget

- Bayesian Biostatistics Conference 2025, 22-24 October 2025, Leiden, The Netherlands.
- 44th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering (MaxEnt), 14-19 December 2025, Auckland, Australia.
- IMS International Conference on Statistics and Data Science (ICSDS), 15-18 December 2025, Seville, Spain. Abstract submission deadline: October 31.
- Joint Meetings of 2025 Taipei International Statistical Symposium and 13th ICSA International Conference, 17-20 December 2025, Taipei, Taiwan. Abstract submission deadline: October 31.

ISBA CANDIDATES 2025

Xinyi Xu
xinyi@stat.osu.edu

ISBA General Elections

President

Long Nguyen	University of Michigan
Judith Rousseau	Université Paris-Dauphine

Treasurer

Leo Duan	University of Florida
Guanyu Hu	Michigan State University

ISBA Board of Directors

Sergios Agapiou	University of Cyprus
Felipe Barrientos	Florida State University
David Dahl	Brigham Young University
Beatrice Franzolini	Bocconi University
Satoshi Morita	Kyoto University
Stéphanie van der Pas	Vrije Universiteit Amsterdam
Alejandra Avalos Pacheco	JKU Linz
Susan Wei	Monash University

J-ISBA Section

Chair-Elect

Reetam Majumder	University of Arkansas
Francesco Gaffi	Bocconi University

Program Chair

Nicolas Bianco	KIT
Yichen Zhu	Bocconi University

Secretary

Elizabeth Louise Bersson	MIT
Jungang Zou	Columbia University
Emma Landry	UCLA

BNP Section

Treasurer

Filippo Ascolani	Duke University
Linxi Liu	University of Pittsburgh

Chair-Elect

Jim Griffin	University College London
Huiyan Sang	Texas A&M University

Program Chair

Antonio Linero	University of Texas at Austin
Tommaso Rigon	University of Milano-Bicocca

BERaP Section

Chair-Elect	
Becky Tang	Middlebury College
Mark Andrews	Nottingham Trent University
Program Chair	
Vanda Inacio	University of Edinburgh
Ron Yurko	Carnegie Mellon University
Secretary	
Shaoyang Ning	Swarthmore College
Jungang Zou	Middlebury College
Treasurer	
Michael Pearce	Reed College

EFaB Section

Chair-Elect	
Roberto Casarin	Ca' Foscari University of Venice
Liana Jacobi	University of Melbourne
Treasurer	
Aubrey Poon	University of Kent
Niko Hauzenberger	University of Strathclyde
Dan Zhu	Monash University
Annika Camehl	Erasmus University Rotterdam
Maria Kalli	King's College London
Nalan Bastürk	Vrije Universiteit Amsterdam

Objective Bayes Section

Program Chair	
Rui Paulo	Universidade de Lisboa
Weining Shen	University of California, Irvine
Treasurer	
Erica Porter	Clemson University
Xiaojin Wang	University of Connecticut

EnviBayes Section

Treasurer	
Whitney Huang	Clemson University
Chair-Elect	
David Bolin	KAUST