MaxEnt 2025

44th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering

University of Auckland
14-19 December

<u>Invited Speakers</u>

Richard Arnold
Ali Mohammad-Djafari
Alexei Drummond
Renate Meyer
Geoff Nicholls

<u>SOC/LOC</u>

Brendon Brewer
Kate Lee
Patricio Maturana Russel
Geraint F. Lewis
Robert Niven
Colin Fox
David Huijser
Paige Chong

www.maxent2025.co.nz

Welcome

We would like to welcome you to New Zealand and to the University of Auckland for the 44th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering. We hope you have a productive meeting and an enjoyable stay. If any issues arise that need our attention, please feel free to email us at maxent2025@auckland.ac.nz.

Kind regards,
The MaxEnt 2025 organising committee

Brendon J. Brewer
Kate Lee
Patricio Maturana Russel
Geraint F. Lewis
Robert Niven
Colin Fox
David Huijser
Paige Chong

Instructions for Speakers

To minimise disruptions and changeover times between talks, please transfer your talk slides to the lectern computer in the break before your session. It is possible to connect your laptop via HDMI for your talk, but it is not our preferred option. Please only do so if your talk cannot be completely exported to PDF (e.g., if there are movies that you need to play). If you plan to do this, please test it first in the break before your session.

Regular contributed talks are allocated 25 minutes in the schedule. Aim for 19–20 minutes for the talk itself, leaving time for a couple of questions.

Locations

The conference itself will be held in the Sir Owen G Glenn Building of the University of Auckland, located on Grafton Road. The conference dinner on Wednesday night is at Top of the Town, inside Pullman Hotel. For lunch, some food vendors at the University of Auckland will be open. You can also find many restaurants in the city, to the west of Albert Park. Note that the walking distance from the Owen G Glenn building to Queen Street (the main road in downtown Auckland) is approximately 1 kilometre and involves some hills. See the map below for more information.

For the excursion (Tuesday afternoon, weather permitting), we will catch a bus from just outside the Owen G Glenn building. The bus will take us to Maungauika/North Head, one of Auckland's volcanic cones, with excellent views of the harbour and the city and some interesting historical military installations. Please be prepared with a hat and sunscreen as New Zealand's summer sunshine can be intense.

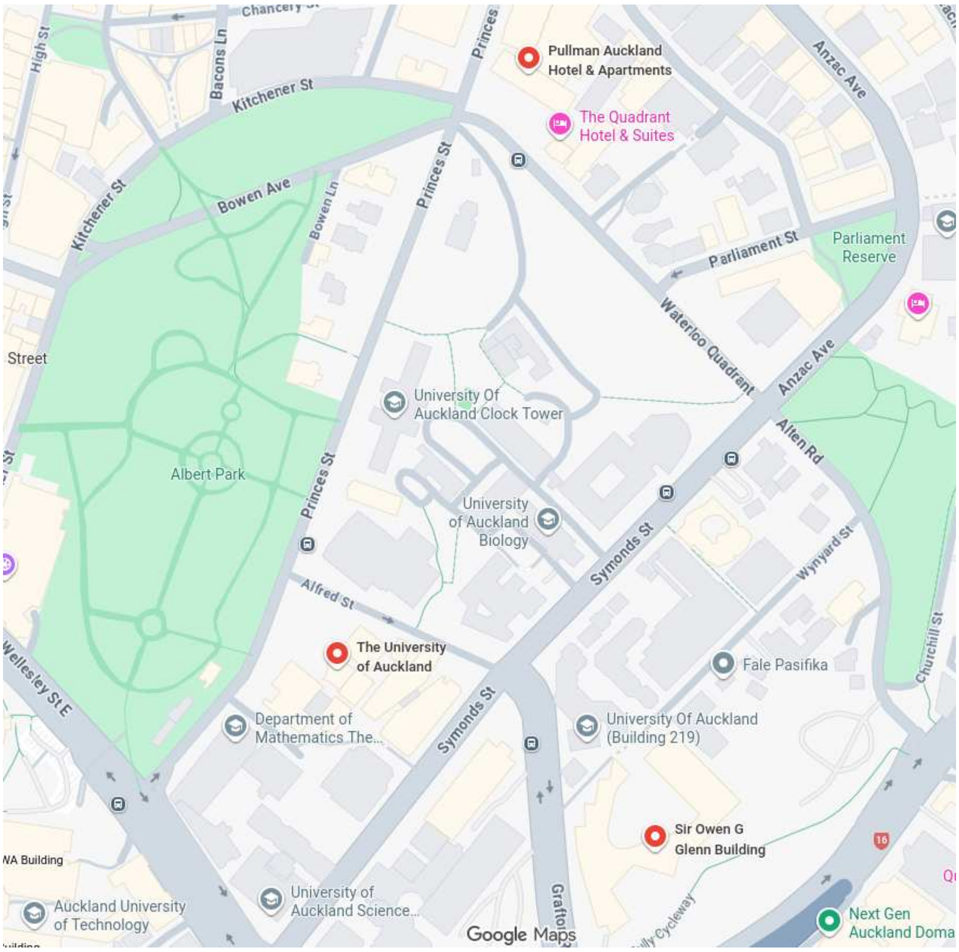

Figure 1: A map showing the location of the conference, the dinner, and some food vendors at the University of Auckland.

Sponsors

We are grateful to the Entropy journal for their support of MaxEnt 2025.

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The conference is also supported by Dr John Skilling.

Schedule

Sunday 14th December (Tutorials)

Location: Decima Glenn (Room 310, Owen G Glenn Building)

12:00	*Foundations of Probability* Robert Niven
13:00	*Positive Monte Carlo — A Nested Sampling Tutorial* John Skilling
14:00	Afternoon Tea
14:30	*Simulation-Based Inference* Kiyam Lin
15:30	*Bayesian Physics Informed Neural Networks for Inverse problems and Digital Twins for Industrial and Biological Application* Ali Mohammad-Djafari (Invited Speaker)
16:30	Finish
18:00	Welcome Reception (Location: 260-071 (Owen G Glenn Building, Level 0 Foyer))

Monday 15th December

Location: OGGB5 (Owen G Glenn Building)

08:45	Welcome
09:00	*Bayesian Phylogenetics and Population Genetics: From Models to Cancer Genomics* Alexei Drummond (Invited Speaker)
09:45	*Bayesian Computation in Inverse Problems, Without MCMC* Colin Fox
10:10	*The Behrens-Fisher Distribution: A Mathematica Certificate for the Derivation of a Closed Form PDF* Barrie Stokes
10:35	Morning Tea
11:00	*Deconvolution of Very Low Signal-to-Noise Poisson Images for Intravital Fluorescent Microscopy* Ioannis Kalaitzidis
11:25	*Counterfactual-informed Adaptive MCMC with Conditional Normalising Flows* Florent Leclerq
11:50	*Likelihood-Free Inference for Epidemiological Agent-Based Modelling: Applications of Approximate Bayesian Computation and Simulation-Based Inference to H3N8 Equine Influenza* James Bristow
12:15	*From Interferometer to Power Spectrum: The Journey of Uncertainties in Detecting an Early Universe Signal* Nichole Barry
12:40	Lunch
14:15	*Computing Bayesian Model Evidences Using Posterior Samples* Zixiao Hu (Tutorial)
15:15	*Predictive Bayes Factors* Shouhao Zhou
15:40	Afternoon Tea

16:10	*Exploring the Rotational Kinematics of M31's Globular Cluster System Using Bayesian Inference* Cher Li
16:35	*Bayesian Model Comparison with the Learned Harmonic Mean for High-Dimensional and Complex Posteriors* Alicja Polanska
17:00	Finish

Tuesday 16th December

Location: OGGB5 (Owen G Glenn Building)

09:00	*Bayesian Non-Parametric Models in Reliability* Richard Arnold (Invited Speaker)
09:45	*Bayesian Hierarchical Models and the Maximum Entropy Principle* Brendon Brewer
10:10	*Bayesian Tree-Mixed Models with Sequential Imputation for Longitudinal Causal Inference* Liangyuan Hu
10:35	Morning Tea
11:00	*Confronting the Cosmological Principle: Shaking the foundations of the Cosmos* Vasudev Mittal
11:25	*Self-Supervised Conformal Prediction with Equivariant Bootstrapping for Uncertainty Quantification in Dark Matter Mass-Mapping* Henry Aldridge
11:50	*Bayesian Regularisation of Inverse RANS problems in Flow-MRI* Claire Namuroy
12:15	*The Wheatstone Bridge Flow Network: Illustrative Example for Maximum Entropy Analysis* Robert Niven
12:40	Lunch
14:15	*Our Symmetries — from Arithmetic to Quantum* John Skilling
14:40	*TOI: Theory of Ignorance* Carlos Rodriguez
15:05	*Deep Polynomial Chaos Expansion* Sascha Ranftl
15:30	Afternoon Tea
16:00	Excursion (North Head)

Wednesday 17th December

Location: OGGB5 (Owen G Glenn Building)

09:00	*Bayesian Nonparametric Methods for the Spectral Analysis of Gravitational Wave Data* Renate Meyer (Invited Speaker)
09:45	*Rapid gravitational wave parameter estimation with data gaps in LISA using conditional flow-matching* Ruiting Mao
10:10	*Bayesian Model Comparison via High Accuracy Marginal Likelihood Estimation Methods in the Pulsar Timing Array* El Mehdi Zahraoui
10:35	Morning Tea
11:00	*On the Cosmic Time Dilation of High-Redshift Quasars* Geraint Lewis
11:25	*Bayesian Tension Quantification of the Cosmic Dipole Anomaly* Mali Land-Strykowski
11:50	*Decoding the cosmic dipole with likelihood-based and likelihood-free inference* Oliver Oayda
12:15	*Unveiling Gravitational Lenses in Colour: A Bayesian Approach to Multiband Inference* Huimin Qu
12:40	Lunch
14:15	*Modeling African Lion Movements and Ecological Corridors Using MaxEnt and Grid-Based Clustering* Atiksh Sah
14:40	*Parameter Learning with Physics-Consistent Gaussian Processes* Johanna Moser
15:05	*Prior Specification for Bayesian Model Averaging in Metabolic Flux Inference : A Dual Statistical–Computational Perspective* Johann Jadebeck

15:30	*Inference for Multi-Messenger Gravitational Wave Lensing* Laura Uronen
15:55	Finish
18:30	Conference Dinner (Location: Pullman Hotel, Top of the Town)

Thursday 18th December

Location: OGGB5 (Owen G Glenn Building)

09:00	*Bayesian Inference for Loss Hyperparameters in Generalised Bayesian Inference* Geoff Nicholls (Invited Speaker)
09:45	*Uncovering Activity Patterns in Free-Living Physical Activity Data from Wearable Devices via a Bayesian Motif-Based Clustering Method* Sin-Yu Su
10:10	*Combinatorial Characterization of Exponential Families of Lumpable Stochastic Matrices* Geoffrey Wolfer
10:35	Morning Tea
11:00	*Visualizing Causal Pathways and Quantifying Marginal and Interaction Effects of Risk Factors on Long-Term Type 2 Diabetes Development: A Conditional Survival Bayesian Network Approach* Mansuk Oh
11:25	*Fast Bayesian Model Comparison Across Multiple Priors and Datasets* Zixiao Hu
11:50	*A New Lens on Gravitational Lens Modelling* Daniel Ballard
12:15	*High-Dimensional Bayesian Inference in Cosmology Through Differentiable Spherical Simulations* Kiyam Lin
12:40	Lunch
14:15	*Spatio-temporal Analysis of Ammonia Concentrations in South Korea Using CrIS Satellite Observations* Bugeon Lee
14:40	*A Methodological Framework for Constructing Digital Biomarkers via Functional Principal Component Analysis of High-Dimensional Functional Activity Data* Ya Han Hsu
15:05	*Bayesian Stability Selection* Mahdi Nouraie

15:30	Afternoon Tea
16:00	*Information Content and Maximum Entropy Reconstruction in Stellar Surface Mapping Inverse Problems* Conaire Deagan
16:25	*A Hierarchical Bayesian Extension of Dynamic Causal Modelling for Evolving Neural Systems* Nilotpal Sanyal
16:50	*Bayesian Model Comparison of Basis Function Systems for Particle Reflection Distribution Data* Udo von Toussaint
17:15	Finish

Friday 19th December

Location: OGGB5 (Owen G Glenn Building)

09:00	*Moment-Generating Funtion Methods in Bayesian Inference* Siyang Li
09:25	*Improved Magnetic Equilibrium Reconstruction and Diagnostic Optimization Using Bayesian Methods on the West Tokamak* Geert Verdoolaege
09:50	*High-Dimensional Uncertainty Quantification with Deep Data-Driven Priors* Jason McEwen
10:15	Morning Tea
10:45	*aim-resolve: Automatic Identification and Modeling for Bayesian Radio Interferometric Imaging* Richard Fuchs
11:10	*Bayesian Multi-Frequency Strong Lensing* Julian Ruestig
11:35	Student Prize Presentation
11:50	MaxEnt International Advisory Committee Meeting

FOUNDATIONS OF PROBABILITY

Robert Niven[1,2]
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(2) UNSW, Canberra, Australia

Abstract

This tutorial examines the probability concept, one of the most important tools of human discovery, and the application of probabilistic inferential methods for the analysis of complex dynamical systems. Tutorial participants will learn - in theory and application - the tremendous power of probabilistic methods (especially Bayesian inference) for the analysis of scientific, engineering and human systems. To do this, it is first necessary to understand the concept of probability. The tutorial will start with a discussion of the different schools of probability, deductive vs plausible reasoning, probabilities as "plausibilities" (the Cox and Jaynes axioms), Bayes' theorem and inverse probabilities. It will also give an overview of orthodox and Bayesian statistical methods and a quick summary of the connection between Bayesian inference and regularization methods.

Positive Monte Carlo — a nested sampling tutorial

John Skilling

Abstract

In statistics and in quantified science generally, the most basic task is adding up the possibilities. In large problems, exhaustive enumeration quickly becomes impractical, so we are forced to adopt sampling methods. The tutorial will develop Nested Sampling as the mature form of simple Monte Carlo sampling.

SIMULATION-BASED INFERENCE

Kiyam Lin[1†], Jason D. McEwen[1,2]

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(2) The Alan Turing Institute, London, UK
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Abstract

In Bayesian parameter inference, accurately modelling data becomes increasingly complex as data fidelity grows, particularly when dealing with computationally intensive calculations such as high-order statistics. To address these challenges, simulation-based inference (SBI) using neural density estimators (NDEs) emerges as a powerful solution. Unlike traditional methods that require direct computation of likelihood functions, SBI enables the learning of posterior distributions, implicit likelihoods, or likelihood ratios directly from simulations, bypassing the need for computationally expensive calculations.

This workshop tutorial will provide an in-depth exploration of neural density estimation approaches within SBI, with a particular focus on two methodologies: neural posterior estimation (NPE) and neural likelihood estimation (NLE). In NPE, we learn the posterior distribution $\mathrm{P}(\theta|\mathrm{data})$ directly, eliminating the need for sampling methods like MCMC or nested sampling. This approach is particularly efficient in scenarios where numerous posterior distributions are required, such as in astrophysics, where each star may have a unique posterior. On the other hand, NLE involves learning the likelihood function, which can then be used with traditional sampling techniques. The use of NDEs in this context makes the forward pass computationally inexpensive and efficient. With NLE, researchers also gain access to a likelihood function that integrates seamlessly with existing workflows and prior choices through amortization. The tutorial will highlight applications of these methods in cosmology and astrophysics, where they offer significant advantages in handling complex models. Additionally, we will discuss methods to obtain Bayesian evidence estimates using only posterior samples such as with the learned harmonic mean estimator (McEwen et al. 2021, Spurio Mancini et al. 2022, Polanska et al. 2023, Polanska et al. 2024a, Spurio Mancini et al. 2024) or in the case of nested models, the Savage-Dickey density ratio with normalizing flows (Lin et al. 2025).

This workshop provides a comprehensive introduction to SBI and NDEs, equipping participants with the knowledge and skills needed to apply these cutting-edge methods effectively in their research across various fields.

Key Words: simulation-based inference, neural density estimation, Bayesian parameter inference, Bayesian evidence estimation.

Bayesian Physics Informed Neural Networks for Inverse problems and Digital Twins for industrial and biological application

A. Mohammad-Djafari

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Chief Scientist, Shanfeng Co. and Institut for Digital Twin (IDT), Ningbo, China

Inverse problems arise almost eberywhere in science and engineering where we need to infer on a quantity from indirect observation. The cases of medical and biomedical imaging are the typical examples. In particular the case of brain imaging from EEG or MEG is a very interesting and famous case.

Digital Twins (DT) are Neural Networks (NN) based dynamical models of industrial or biological systems which have been pre-trained with some historical data, but can be easily updated and used with real time data to do prediction about the behavior of the system.

A very high overview of classification of the inverse problems method can be: i) Analytical, ii) Regularization, and iii) Bayesian inference methods. Even if there are straight links between them, we can say that the Bayesian inference based methods are the most powerful, as they give the possibility of accounting for prior knowledge and can account for errors and uncertainties in general. One of the main limitations stay in computational costs in particular for high dimensional imaging systems. Neural Networks (NN), and in particular Deep NNs (DNN), have been considered as a way to push farther this limint.

Physics Informed Deep Neural Networks (PIDNN) concept integrates physical laws with deep learning techniques to enhance the speed, accuracy and efficiency of the above mentioned problems. The main idea behind this concepts can be summarized as follows:
– DNNs are universal *function approximators*. Therefore a DNN, provided that it is deep enough, can approximate any function: the solutions of inverse problems or those of the differential equations (ODE and PDE).
– Computing the derivatives of a DNN output with respect to any of its input (and the model parameters during backpropagation), using *Automatic Differentiation* (AD), is easy and cheap. This is actually what made DNNs so efficient and successful.
– Usually DNNs are trained to fit the data, but do not care from where come those data.
– Physics based or Physics Informed: If, *besides fitting the data, fit also the equations that govern that system and produce those data*, their predictions will be much more precise and will generalize much better.

In this tutorial, the focus will be on a new Bayesian framework for the concept of PINN (BPINN), which is used for now for industrial applications, but will also be used to biological applications, in particular in Brain imaging.

Main References:

1 Deep Learning and Inverse Problems [arxiv:2309.00802]

2 Deep Learning and Bayesian inference for Inverse Problems [arxiv:2308.15492]

3 Raissi M, Perdikaris P, Karniadakis GE. A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 378, 686-707 (2019), [arXiv:1711.10561], and [arXiv:1711.10566]

4 George Em Karniadakis, Ioannis G. Kevrekidis, Lu Lu, Paris Perdikaris, Sifan Wang and Liu Yang, Physics informed machine learning, Nature Reviews Physics 3, 422–440 (2021)

BAYESIAN PHYLOGENETICS AND POPULATION GENETICS: FROM MODELS TO CANCER GENOMICS

A. Drummond[1]
(1) Centre for Computational Evolution, The University of Auckland, Auckland, New Zealand

Abstract

Recent advances in Bayesian methods have significantly improved our ability to model evolutionary and population genetic processes. In this seminar, I will outline recent developments in domain-specific modeling languages, designed to simplify and enhance model specification in phylogenetics and population genetics. Additionally, I will introduce new approaches to posterior analysis in phylogenetic tree space, providing clearer interpretation and visualization of complex posterior distributions. To illustrate these methods, I will discuss their application to single-cell sequencing data from cancer, enabling joint inference of genotypes and cell lineage trees, thus revealing detailed insights into tumour evolution.

BAYESIAN COMPUTATION IN INVERSE PROBLEMS, WITHOUT MCMC

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Abstract

Computational MCMC (Markov chain Monte Carlo) has been a mainstay of provably-correct Bayesian computing for some decades, with the significant drawback of being computationally intensive. We are now able to bypass MCMC completely, and compute posterior expectations in hierarchical Bayesian formulations of inverse problems using just function approximation and numerical quadrature, for much lower compute cost.

Recent advances in numerical linear algebra, particularly the tensor-train (TT) representation, allow high-dimensional function representation and subsequent numerical integration (and also sampling, if you want it) with cost that is linear in dimension [1]. We combine TT methods with the 'marginal then conditional' factorisation [2] to demonstrate full posterior inference over a physically-based hierarchical model with nonlinear observation process (recovering stratospheric ozone profiles from emission data), using zero sampling.

References:

[1] S. Dolgov K. et al. Statistics and Computing, **30**(3) 603-625 (2020).

[2] C. Fox et al. SIAM/ASA JUQ **4**(1) 1191-1218 (2016).

Key Words: Functional tensor train, inverse problem, posterior inference, no MCMC, limb sounding

The Behrens-Fisher Distribution: A Mathematica Certificate for the Derivation of a Closed Form PDF

B.J Stokes*
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Suppose we have two small data sets of size n_1 and n_2, each of which we model as a random sample from a Gaussian distribution, the one being $N(\mu_1, \sigma_1)$ and the other $N(\mu_2, \sigma_2)$. Interest is in the difference $\delta = \mu_1 - \mu_2$ while treating the standard deviations σ_1 and σ_2 as unknown. This model is common in many experimental settings, such as medicine and agriculture.

If σ_1 and σ_2 are assumed unknown but *equal*, the problem is the two-sample problem. The test statistic is a suitably scaled difference of the sample means and is distributed as a Student *t* variate.

If they are assumed unknown and *unequal*, the problem is the Behrens-Fisher problem. The test statistic *d* is a weighted difference of two Student *t*-distributed statistics, with degrees of freedom $\nu_1 = n_1 - 1$ and $\nu_2 = n_2 - 1$. Behrens (1929) gave the first treatment of this problem, and Fisher (1935) developed his fiducial inference approach in order to apply it to this problem.

Much effort has been expended on devising approximations to the distribution of *d*, since for many years a closed form expression for the Behrens-Fisher PDF could not be found. However, Rahman & Saleh (1974a, 1974b) managed to derive a closed form by constructing and then inverting the characteristic function of the statistic *d*.

We have used a computer algebra system to produce a *Mathematica* "Certificate" for Rahman & Saleh's derivation, in the process revealing several typographical errors in their main paper (1974a) and in their Corrigendum (1974b). Indeed, their final PDF expression as printed is incorrect.

The construction of the *Mathematica* "Certificate" will be sketched very briefly, and some relevant datasets studied in Bretthorst (1993) and Gregory (2005) will be reviewed using this Behrens-Fisher distribution.

Behrens W.-V. (1929). Landwirtschaftliche Jahrbücher. 68, 807-37.

Bretthorst, G. Larry. (1993). In Physics & Probability: Essays in honour of Edwin T. Jaynes, W. T. Grandy & P. W. Milonni (eds.) Cambridge University Press, 177-194.

Fisher, R. A. (1935). Annals of Eugenics 6, 391-398.

Gregory, P.C. (2005). *Bayesian Logical Data Analysis for the Physical Sciences*. Cambridge University Press.

Rahman, M. & Ehsanes Saleh, A. K. Md. (1974a). J. Roy. Stat. Soc. 36, 1, 54-60.

Rahman, M. & Ehsanes Saleh, A. K. Md. (1974b). J. Roy. Stat. Soc. 36, 3, 466.

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Deconvolution of very low signal-to-noise Poisson images for *intravital* fluorescent microscopy

Y.Kalaidzidis

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A very low signal-to-noise ratio (SNR < 5) is a common challenge in *intravital* confocal fluorescence microscopy, where both limited excitation laser intensity—constrained by phototoxicity—and high scanning speed result in as few as 1 to 5 photons per pixel [1]. Deconvolution with regularization is a classical approach to improving microscopy resolution while simultaneously denoising the image. Unfortunately, in the case of very low SNR, this approach becomes ineffective, as the high weight of regularization term that is required also suppresses the deconvolution itself.

To address this issue, we propose a combination of a context-aware nonlinear denoising filter based on Kolmogorov–Arnold Networks (KAN) [2] implementation of Noise2Voild [3] neural network and deconvolution using a Laplacian likelihood with a MaxEnt prior. The KAN architecture allowed to limit number of trainable network parameters to only ~28,000. Such small network can be trained from scratch in ~5 minutes on a single image to be processed. After denoising the weight of the MaxEnt prior is robustly estimated as function of the ratio of the local proximity intensity projection along the point spread function (PSF) to the mean projection in directions perpendicular to the PSF.

The proposed pipeline was applied to high-resolution hisgh frequency *intravital* imaging of bile canaliculi in mouse liver. The deconvolved time-lapse sequences revealed the dynamics of submicron "bulkhead" structures [4], which are essential for regulating elevated pressure in the liver's biliary system.

[1] Meyer, K., Ostrenko, O., Bourantas, G, et al., Cell Systems, 4(3), 277-290 (2017)
[2] Liu, Z., Wang, Y., Vaidya, S., et al., arXiv: 2404.19756v3 (2024)
[3] Krull, A., Buchholz, T.O., Jug, F., ArXiv, 1811.10980v2 (2019)
[4] Mayer, C., Nehring, S., Kuecken, M., et al., EMBO reports, 24, e57181 (2023)

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Counterfactual-informed adaptive MCMC with conditional normalising flows

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Abstract

Markov Chain Monte Carlo (MCMC) methods are particularly powerful as they can correct for their mistakes via the Metropolis–Hastings (MH) acceptance test, providing an asymptotic guarantee of convergence to the target distribution. A key ingredient is the proposal distribution, which determines sampling efficiency. However, theory offers no general prescription for designing such a proposal distribution. In high-dimensional settings, one often finds that any naïve proposal yields no accepted samples which could be used as training data. Moreover, if the data model is non-differentiable, gradients are also unavailable as training data.

We address the automatic design of a proposal distribution in scenarios where naïve choices result in near-zero acceptance rates and gradients cannot be employed. Specifically, we consider models comprising a signal (an arbitrary, non-differentiable function of the parameters) and additive Gaussian noise. We present a geometric interpretation of the MH test in this context, showing that each test defines a hyperplane that partitions data space into acceptance and rejection regions. We demonstrate that a rejection in the MCMC of interest would correspond to an acceptance in an alternative chain if the true data vector were replaced by a suitably chosen alternative data vector, close in the Mahalanobis sense.

Building on this insight, we introduce a novel MCMC algorithm that augments traditional MH sampling with "reasoning with counterfactuals." By recording not only {accepted parameter, true data} pairs, but also {rejected parameter, alternative data} pairs that would have led to acceptance, we construct a replay buffer for training a conditional normalising flow. This normalising flow serves as an independence proposal alongside a vanilla random-walk proposal. The result is a general-purpose, adaptive MCMC method with a proposal distribution that self-improves by learning from both accepted and rejected moves. We evaluate the performance of our algorithm on challenging Bayesian inference tasks, including field-level inference in cosmological data analysis.

Likelihood-Free Inference for Epidemiological Agent-Based Modelling: Applications of Approximate Bayesian Computation and Simulation-Based Inference to H3N8 Equine Influenza

J. Bristow[a,*], M. Vignes[a], and D. Hayman[b]

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[b]*School of Veterinary Science, Massey University, Palmerston North, New Zealand*

Agent-based models (ABMs) can simulate complex interactions between individuals to help inform public health policy. ABMs facilitate the incorporation of spatiotemporal structure, individual-level heterogeneity, and behavioural variability. While ABMs are invaluable tools for epidemiological planning, it is necessary to validate them using empirical data to bolster confidence that these models yield realistic predictions for informing policy decisions. Moreover, the application of uncertainty quantification methods is required to provide robust parameter estimates and model predictions. However, fitting ABMs to empirical data (calibration) can prove challenging due to model complexity, equifinality, and stochasticity. Bayesian calibration is one such approach for performing parameter estimation and uncertainty quantification on complex simulation models. Here, we have developed a compartmental ABM to simulate the diffusion dynamics of infectious diseases over time and space. The case study with which we have validated our model is the 2019 outbreak of H3N8 equine influenza within Great Britain. We present the use of two likelihood-free algorithms to perform Bayesian calibration: (1) Approximate Bayesian Computation Sequential Monte Carlo and (2) Flow Matching Posterior Estimation. We further demonstrate a generalisation of Approximate Bayesian Computation random forest, which we use to perform both model selection and a sensitivity analysis of epidemiological quantities derived from our ABM. For our preliminary results, we found that Flow Matching Posterior Estimation produced the better fitting model, and that our ABM was most sensitive to variation in attack rate.

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FROM INTERFEROMETER TO POWER SPECTRUM: THE JOURNEY OF UNCERTAINTIES IN DETECTING AN EARLY UNIVERSE SIGNAL

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Abstract

The early Universe glows faintly due to primordial neutral hydrogen. When the first stars and galaxies form, they slowly ionize this hydrogen, thereby ceasing the glow. By measuring this "Epoch of Reionisation," we can access the the most basic experimental setup we will ever have at the intersection of cosmology and astrophysics models. This signal is hypothetically extractable in Fourier space, and thus interferometers around the world are pursuing the first power spectrum detection of this time period. However, the primordial hydrogen signal from the Epoch of Reionisation is fainter than a light bulb on Pluto in the middle of a fully lit stadium, and thus the search requires a delicate intersection of precision, sensitivity, and advanced mathematical techniques. Understanding how to perform the order-petabyte data reductions whilst reducing the causes of contamination that render the signal immeasurable is the focus of my research. In particular, I will discuss the efforts to propagate the uncertainties from the Fourier measurement through to the maximum likelihood of the power spectrum as a robust verification. I will discuss the complicated relationship our community has with more sophisticated priors, and how extracting the faint signal has been a battle of retractions and slow progress.

COMPUTING BAYESIAN MODEL EVIDENCES USING POSTERIOR SAMPLES

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(2) The Alan Turing Institute, London, UK
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Abstract

Bayesian model comparison provides a principled framework for evaluating competing models by trading off complexity and goodness of fit. It requires computing the Bayesian model evidence or marginal likelihood, which is a challenging high-dimensional integral over parameter space. Traditional approaches like nested sampling are highly effective and have been instrumental in advancing Bayesian model comparison. However, these are inherently coupled to specific sampling strategies, which can limit integration with existing MCMC workflows. Many researchers possess posterior samples from preferred methods but lack tools to compute model evidences from these samples.

The learned harmonic mean estimator addresses these limitations by requiring only posterior samples as input, making it agnostic to the sampling strategy [1,2]. Whether samples come from ensemble methods, Hamiltonian Monte Carlo, or other MCMC techniques, the method computes reliable evidence estimates. It uses machine learning to approximate the posterior distribution, avoiding catastrophic failures of the original harmonic mean estimator. The method is implemented in the Python package `harmonic`, which is open-source and designed following best practices.

This tutorial is designed for early-career researchers and provides a step-by-step walkthrough in a Jupyter notebook, showing how to compute Bayesian evidences with posterior samples. Participants will gain a conceptual understanding of the estimator, as well as practical skills to apply scientific model comparison in their own research.

References:

[1] McEwen, J.D. et al. (2023). doi.org/10.48550/arXiv.2111.12720

[2] Polanska, A. et al. (2024). doi.org/10.48550/arXiv.2405.05969.

Key Words: Bayesian model comparison, machine learning

Predictive Bayes Factors

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(1) Pennsylvania State University
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Abstract

We are concerned with the comparison of Bayesian posterior models using model probabilities. By taking a cross-validative view of a general predictive density form, we attempt to explain the role of data in the method of Bayes factors. We vindicate that the method of Bayes factors may have been extensively misused by evaluating models with model parameters fixed at the prior distribution rather than the posterior distribution. If the models of interest are with parameter distributions updated to posterior by the observed data, traditional Bayes factor approaches may not be feasible. A new entropy-based method, called the "predictive Bayes factor", is introduced, to approximate the ratio of out-of-sample posterior predictive distribution, for comparison of the posterior models. In principle, it soundly avoids Lindley's paradox in testing point null hypothesis with composite alternative hypothesis. In practice, the predictive Bayes factor substantially reduces sensitivity to variations in the prior of the parameters and, without using cross-validation, is computationally efficient. Simulation results are also obtained to gain some understanding on the small sample properties.

Exploring the Rotational Kinematics of M31's Globular Cluster System Using Bayesian Inference

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Previous studies on globular clusters (GCs) in the inner and outer regions of the Andromeda galaxy (M31) have identified distinct subpopulations with unique kinematic properties. This research applies Bayesian inference and Nested Sampling to examine the combined GC population's dynamics and kinematics. The primary objective is to investigate how metallicity and substructure status (whether a GC is associated with a substructure) affect the rotational characteristics of M31 GCs, and to determine whether the combined dataset reveals consistent behaviour compared to separate analyses of the inner and outer GCs. The findings indicate that metal-poor GCs and those associated with substructures rotate more rapidly and in a different direction than metal-rich and non-substructure GCs. Furthermore, metal-rich GCs were found to rotate in the same direction as Andromeda's stellar disc. These distinct kinematic patterns suggest that different GC subgroups were accreted onto M31 at different times, offering valuable insights into the galaxy's complex assembly history.

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BAYESIAN MODEL COMPARISON WITH THE LEARNED HARMONIC MEAN FOR HIGH-DIMENSIONAL AND COMPLEX POSTERIORS

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Abstract

Computing the Bayesian evidence is an important task in Bayesian model selection, providing a principled quantitative way to compare models. In this work, we apply and further develop the learned harmonic mean estimator of the Bayesian evidence with normalizing flows. This recently presented estimator leverages machine learning to address the exploding variance problem associated with the original harmonic mean. The improved method provides an accurate, robust and scalable estimator of the Bayesian evidence. Moreover, it is agnostic to the sampling strategy, meaning it can be combined with various efficient MCMC sampling techniques or variational inference approaches. We present numerical experiments demonstrating the effectiveness of the use of normalizing flows for the learned harmonic mean and apply the method to practical examples in cosmological and gravitational wave astrophysics settings. We perform a 37-dimensional cosmic shear analysis using CosmoPower-JAX, a JAX-based implementation of the CosmoPower framework that accelerates cosmological inference by building differentiable neural emulators of cosmological power spectra, observing significant speed-up compared to the conventional method. We also successfully perform cosmological analysis in a 157-dimensional setting, where using conventional methods is not feasible. We also estimate the evidence of a gravitational wave signal from binary black hole merger with a 4- and 11-dimensional parameter space, where the posterior is complex and multimodal. Thanks to the accelerated JIM inference pipeline with normalized flow assisted sampling, we are able to significantly reduce the computational cost, but retain the ability to perform model comparison thanks to the learned harmonic mean. By leveraging advanced flow architectures, we are able to extend this type of analysis to high dimensional, and complex multimodal posteriors. This shows that coupled with scalable samplers, the learned harmonic mean estimator has the potential to allow for the comparison between models of unprecedented complexity, thus unlocking the full potential of Bayesian analysis even in high-dimensional settings.

Bayesian non-parametric models in reliability

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Abstract

In this talk we will discuss two applications of Bayesian non-parametric modelling to problems in reliability theory.

In the first application we use data from software reliability, in which a piece of software is tested independently by a panel of reviewers. Each reviewer has a different level of skill, and the faults have different levels of detectability. Our goal is to simultaneously cluster the reviewers into groups of similar skill, and faults into groups of similar detectability, and ultimately estimate the number of faults which have not been detected. This setting is equivalent to capture-recapture problems incorporating heterogeneity. One common approach to this problem is to specify a biclustering finite mixture model. In this instance we instead use the Dirichlet Process Prior as the generative model for the detection of each fault by each reviewer, and then *a posteriori* we group the reviewers and faults.

In the second application we consider the non-parametric estimation of bathtub hazard rate functions. A bathtub function consists of a high initial failure rate, equivalent to the high infant mortality rate shared both by animals and manufactured systems, after which the hazard rate decreases to a period of rare failures. Finally the hazard rate increases towards the end of the life of the system. In this case we use the Gamma Process Prior as the basis of a number of different specifications of such bathtub shaped hazard rates.

BAYESIAN HIERARCHICAL MODELS AND THE MAXIMUM ENTROPY PRINCIPLE

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Abstract

Bayesian hierarchical models are frequently used in practical data analysis contexts. One interpretation these models is that they provide an indirect way of assigning a prior for unknown parameters, through the introduction of hyperparameters. The resulting marginal prior for the parameters usually has a dependence structure, so that, for example, learning one parameter provides some information about the values of the others. In this talk, I will demonstrate that, in two common scenarios, the same dependent prior can be derived through the application of maximum entropy (Jaynes 2003, Caticha 2021). The most familiar kind of constraint for maximum entropy is a constraint on expected values. However, to achieve the equivalent distribution through maximum entropy, the constraint needs to be about the *marginal distribution* of a function of the unknown parameters. The results shed light on what information is actually being assumed when we assign a hierarchical model.

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Key Words: BAYESIAN INFERENCE, MAXIMUM ENTROPY, PRIOR DISTRIBUTIONS

Bayesian Tree-Mixed Models with Sequential Imputation for Longitudinal Causal Inference

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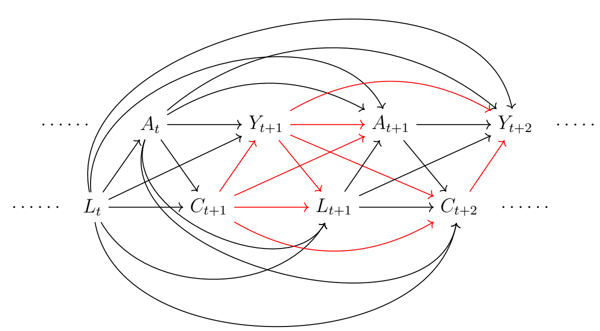
Abstract

Longitudinal treatment studies often suffer from intermittently measured covariates and complex time-varying confounding (illustrated in the accompanying figure), making causal estimation highly sensitive to parametric assumptions. We propose a Bayesian non-parametric framework that first performs maximum-entropy, sequential imputation of the missing covariate history with an ensemble of Bayesian regression trees plus subject-specific random effects, flexibly capturing nonlinear trends and heterogeneity. Building on these completed trajectories, we introduce a new, computationally light Bayesian g-formula that integrates over the full posterior to produce treatment-specific counterfactual outcomes, fully propagating imputation uncertainty without additional latent variables. The method cleanly separates latent-data augmentation for observed-but-missing covariates from purely predictive draws for counterfactual responses, thereby addressing complex time-varying confounding in a single coherent step. Extensive simulations confirm bias reduction and nominal credible-interval coverage compared with parametric multiple imputation followed by standard g-computation. We employ our methods on a cardiovascular disease study dataset, aiming to determine and validate the most effective rules for initiating antihypertensive treatment.



Key Words: Bayesian nonparametrics, Missing data, Causal inference, Longitudinal study, Optimal treatment regime

Confronting the Cosmological Principle: Shaking the foundations of the Cosmos

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This talk intends to put the Cosmological Principle (CP) to test by analyzing all-sky surveys of quasars and radio galaxies. CP asserts that the universe is isotropic and homogeneous on large scales. It attributes the Cosmic Microwave Background (CMB) thermal dipole to our local peculiar motion [1], hence giving it the name of kinematic dipole. If this attribution is correct, then all sky surveys of other cosmological probes should show a similar dipole in their distribution throughout the sky. More than forty years ago, researchers postulated the presence of a number count dipole in source distribution (dubbed as the matter dipole) as a test for the CP [2]. However, recent research [3] has found a disagreement between the matter dipole and kinematic dipole, with claims reaching well over 5σ! [4,5] I will put the CP to test by analysis of all sky surveys of quasars [6] and radio galaxies [7,8]. Using Bayesian statistics, I will show that a dipole aligned with the CMB is present. However, the amplitude of the dipole is still in tension with our expectations, bringing the validity of the cosmological principle into question [9,10]. We will also look into the future, discussing some outstanding issues in the domain and possible methods to increase the sophistication of the number count dipole test. [11,12].

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SELF-SUPERVISED CONFORMAL PREDICTION WITH EQUIVARIANT BOOTSTRAPPING FOR UNCERTAINTY QUANTIFICATION IN DARK MATTER MASS-MAPPING

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Abstract

Inverse problems involve recovering an underlying value from noisy observations often transformed by a measurement operator. These problems are frequently ill-posed, particularly in imaging, leading to multiple plausible solutions and considerable uncertainty in reconstructed images. In fields like the physical and biological sciences, accurate uncertainty quantification (UQ) is critical for precise measurements and confident diagnoses. Current UQ methods for imaging often fall short; they can be inaccurate, or require unavailable or difficult-to-acquire ground truth data for calibration, which also leads to a lack of robustness to distribution shifts between calibration and observed data. We introduce an UQ approach that leverages equivariant bootstrapping [1] to generate marginal coverages by exploiting data symmetries. We then refine these coverages through a conformal prediction calibration step in a manner akin to [2], but crucially employing a self-supervised approach [3] to avoid the need for ground truth calibration data. We demonstrate this method with dark matter mass-mapping, where we aim to reconstruct the convergence field from shear measurements of distant galaxies weakly-lensed by gravitational fields. Mass-mapping in particular benefits from the self-supervised approach, as simulating calibration data is expensive and relies on specific cosmological models that could introduce biases in downstream cosmological inference tasks.

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Key Words: Inverse Problems, Imaging, Cosmology

Bayesian regularisation of inverse RANS problems in Flow-MRI

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Magnetic Resonance Imaging (Flow-MRI) is an experimental technique for measuring blood velocities in time and space. The method however suffers from coarse spatiotemporal resolution and low signal-to-noise ratios, which limit the accuracy of the observations. The noise-free, fully-resolved velocity fields can be recovered by enforcing the Navier-Stokes equations, along with additional eddy viscosity models to capture momentum transport due to turbulent flow. In this study, we formulate an inverse Reynolds-averaged Navier-Stokes (RANS) problem for the time-averaged velocity fields given noisy velocimetry data. The forward model is parametrised by the flow domain, the boundary conditions of the RANS equations and the parameters of the eddy viscosity model. To regularise the inverse problem, we apply Bayes' rule. We specify Gaussian priors for the parameters and Gaussian measurement noise. Adopting the Laplace approximation, Maximum-A-Posteriori (MAP) estimates of the model parameters and their uncertainties are then computed using a quasi-Newton method. The gradients of the model outputs with respect to their parameters, which are used for both calculations, are obtained efficiently using adjoint methods. We apply this framework to assimilate experimental observations of the mean flow through an idealised medical device (FDA nozzle) into two RANS models: (1) a 5-parameter algebraic model, and (2) an 8-parameter one-equation model. The proposed algorithm not only achieves accurate data reconstruction, it also enables the estimation of hidden flow quantities, such as wall shear stress and pressure, that are of clinical interest. The methodology can further be extended to more complicated turbulence models under the condition that they are differentiable.

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The Wheatstone Bridge Flow Network: Illustrative Example for Maximum Entropy Analysis

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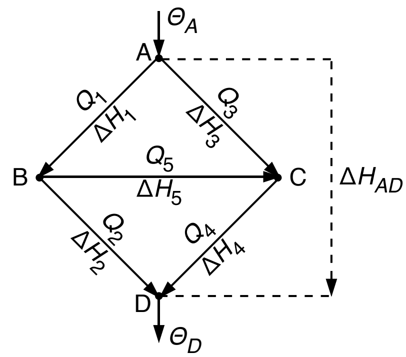
Abstract



This study applies the maximum entropy (MaxEnt) method to the prediction of flow rates and potentials on a potential-driven flow network, such as a water distribution or electrical network. We examine the Wheatstone bridge network above, to provide a computationally tractable network, which permits many nuances for different choices of constraints. The network contains 5 internal flow rates $\{Q_i\}$, 2 external flow rates $\{\Theta_A, \Theta_D\}$, 5 internal potential differences $\{\Delta H_i\}$ and a potential difference across the network ΔH_{AD}, connected by resistance functions $\Delta H_i = R(Q_i)$ for each edge i. Applying the MaxEnt method, we maximise the relative entropy subject to various constraints, including (a) known resistance functions and a known input flow rate, both for linear or nonlinear resistances, and (b) various settings with 1 unknown resistance function. Using a multivariate Gaussian prior, the MaxEnt formulation is analytic, even for nonlinear resistance functions, so does not require the numerical solution method reported in previous studies [1]. The analysis is constructed to develop an illustrative example of the MaxEnt method, for comparisons to Bayesian inference of the same problem (in future studies).

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Key Words: MaxEnt analysis, Bayesian inference, flow network, prior, constraints

Our Symmetries — from Arithmetic to Quantum

John Skilling

Abstract

In science, we abstract from the complexity of the external world by making intellectual models. Abstraction involves simplification by using symmetries such as associativity (so that a composite object is deemed independent of the order of its assembly). In symbols,

(A and B) and C = A and (B and C)

and so on. These elementary symmetries, intrinsic to our modelling, underlie the ordinary arithmetic of addition and multiplication which we develop into standard mathematics.

In physics, though, quantification is inseparable from uncertainty. That means that modelling needs to be be based on pairs of numbers (our "pair postulate"). That calculus of pairs has three product rules. One of them is recognised as multiplication of complex numbers. That is the only rule which allows probabilistic inference, which explains why our physics has to be based on complex numbers. The other two rules, now applied to complex numbers, generate the Lorentz group, whose structure was empirically discovered a century ago as the quantum equations of relativistic momentum and spin. Meanwhile, complex phase can be identified as time. These are the founding equations of quantum formalism.

The behaviour of complex objects follows that of the constituents. Our sensory experience naturally follows that as we learn to make sense of the world in early infancy. That is why we perceive the world as having three spatial dimensions. Relativistic spacetime in 3+1 dimensions is not just empirically "obvious" — it is intellectually required.

TOI: THEORY OF IGNORANCE

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Abstract

The problem with Bayesianism are the priors. There is still no general theory for choosing the prior. The purpose of this paper is to provide such a theory. This is made possible by a new geometrization of the concept of ignorance. At the same time this forces a re-evaluation of the meaning of data, of prior, and indeed the meaning of meaning itself. It turns out to be surprisingly simple: Probability is meaning.

DEEP POLYNOMIAL CHAOS EXPANSION

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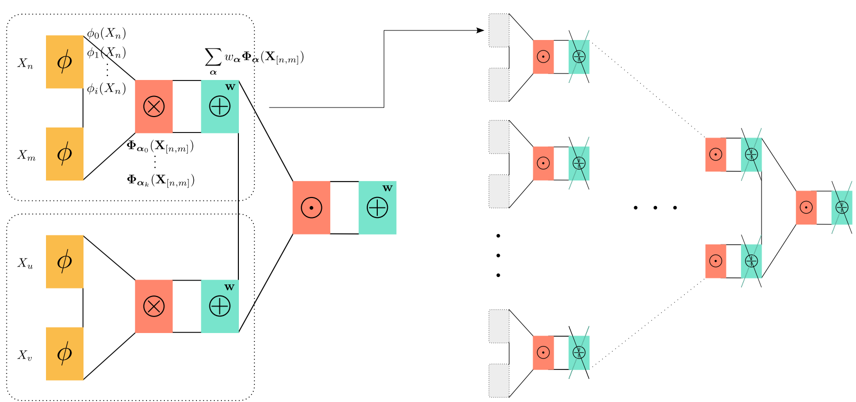
Abstract

Polynomial chaos expansion (PCE) is a classical and widely used surrogate modeling technique in physical simulation and uncertainty quantification [1]. By taking a linear combination of a set of basis polynomials orthonormal with respect to the distribution of uncertain input parameters, PCE enables tractable inference of key statistical quantities, such as (conditional) means, variances, covariances or Sobol sensitivity indices. As the number of basis functions grows exponentially with the number of parameters, PCE does not scale well to high-dimensional problems. We address this challenge by combining PCE with ideas from probabilistic circuits [2], resulting in the *deep polynomial chaos expansion* (DeepPCE): A deep generalization of PCE that scales effectively to high-dimensional input spaces. DeepPCE achieves predictive performance comparable to that of multi-layer perceptrons (MLPs), while retaining PCE's ability to compute *fast, exact* statistical inferences via simple forward passes.



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Key Words: probabilistic deep learning, polynomial chaos, surrogate modeling

BAYESIAN NONPARAMETRIC METHODS FOR THE SPECTRAL ANALYSIS OF GRAVITATIONAL WAVE DATA

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Abstract

The new era of gravitational wave astronomy truly began on September 14, 2015, with the groundbreaking first direct detection of gravitational waves, when LIGO recorded the signal from the merger of two black holes. This discovery confirmed a major prediction of Einstein's general theory of relativity and opened an entirely new observational window onto the universe. Since then, across four observing runs by the LIGO/Virgo/KAGRA network, gravitational waves from approximately 300 compact binary mergers have been reported. Ongoing efforts are improving the sensitivity of current ground-based detectors, while next-generation observatories such as the Einstein Telescope and the Cosmic Explorer are being planned. In addition, the future Laser Interferometer Space Antenna (LISA) will observe gravitational waves from space and open the low-frequency window of gravitational wave detection, enabling the observation of a wide range of sources—including white dwarf binaries within the Milky Way and mergers of supermassive black holes at the centres of galaxies. However, approximately ten years before the launch of the LISA mission, the scientific community is still far from solving some of the major methodological and computational challenges that will determine the mission's success.

Realizing the full scientific potential of these observations requires careful statistical analysis, particularly in characterizing the background noise by accurately modelling spectral features. This review will cover the fundamentals of gravitational wave data analysis, with an emphasis on LISA. Key challenges in this new data analysis regime will be highlighted, and novel Bayesian nonparametric methods for spectral density estimation of correlated and locally stationary noise will be proposed.

Rapid gravitational wave parameter estimation with data gaps in LISA using conditional flow-matching

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Abstract

The Laser Interferometer Space Antenna (LISA) promises to revolutionise gravitational wave astronomy, yet its data will inevitably suffer from gaps and instrumental noise. These discontinuities corrupt the signal, introducing non-stationary noise, making traditional parameter estimation via Whittle likelihood and Markov Chain Monte Carlo (MCMC) computationally expensive and prone to bias. While our previous work introduced a hybrid stacked autoencoder to repair the idealised signal component and accelerate subsequent Bayesian analysis [1], the presence of instrumental noise in realistic scenarios demands a more direct and robust approach.

To address this, we present a novel framework that conducts a Simulation-Based Inference (SBI) with conditional flow-matching to perform parameter estimation directly on noisy, incomplete signals. To manage the high dimensionality of LISA data, we extend our previous dimension reduction technique [2], which derives a compressed, low-dimensional feature representation of the signal, streamlining the likelihood-free inference in the time domain. Furthermore, we speed up the training by adapting the proposed methodology to the wavelet domain.

Validated on simulated Galactic Binary signals, our model demonstrates rapid and accurate performance, yielding posterior distributions comparable to those from MCMC on complete data. Our exploration with data gaps in LISA, therefore, presents a complete and computationally efficient solution for gravitational wave parameter estimation in the presence of realistic data artefacts, a critical step for maximising the scientific return of the LISA mission.

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Key Words: Gravitational waves, Data gaps, Simulation-Based Inference, Likelihood-free inference, Flow-matching, Laser Interferometer Space Antenna

Bayesian Model Comparison via high-accuracy marginal likelihood estimation methods in the Pulsar timing Array.

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Abstract

Bayesian model comparison relies fundamentally on the accurate estimation of marginal likelihoods (also known as model evidences), which underpin Bayes factors. However, precise computation of these integrals is challenging, especially in high-dimensional or complex models. Building on recent work in gravitational-wave data analysis[1], we present a comprehensive evaluation of high-accuracy marginal likelihood estimation methods. Through simulation and gravitational-wave analysis in the Pulsar Timing Array, we assess the new method's performance across varying sample sizes, model dimensionality, and posterior complexity. Our results highlight the substantial performance of high-accuracy methods over traditional and widely adopted methods in computational effort, bias reduction, and variance control. This work underscores the critical role of modern marginal likelihood estimation techniques in enabling robust Bayesian inference.

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Key Words: Bayesian methods, Marginal likelihood, Evidence estimation.

On the cosmic time dilation of high-redshift quasars

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In this talk, we present a Bayesian statistical analysis of high-redshift quasar light curves to search for the influence of cosmic time dilation. Due to the expansion of our universe, temporal process of distant sources should be subject to cosmic time dilations, with all times stretched by a precise factor of $(1+z)$, where z is the redshift. While this phenomenon has been observed in the brightening and fading of distant supernovae, the presence of time dilation variability of supermassive black holes at the hearts of quasars, some of the most luminous objects in the universe, remains contentious. Using hierarchical models and Bayesian model comparison, we separate intrinsic variability from cosmological signals while accounting for observational noise and selection biases. Our results highlight the effectiveness of Bayesian inference in extracting subtle temporal signatures from complex astrophysical data, offering new insights into both quasar variability and the fundamental properties of our expanding universe.

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Bayesian Tension Quantification of the Cosmic Dipole Anomaly

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Abstract

The cosmic dipole observed in surveys of distant extragalactic sources consistently diverges from the kinematic dipole inferred from the CMB, posing a serious challenge to the Cosmological Principle and the standard model of cosmology. In this talk, I present a state-of-the-art Bayesian analysis of this tension, leveraging data from radio surveys - NVSS and RACS - and WISE IR cosmological sources, alongside *Planck* CMB observations. Our joint analysis corroborates the recent challenge against the standard model and reveals discordance between RACS and the other catalogues, suggesting the presence of a systematic effect. Through simulations, we show that next-generation SKA surveys could decisively confirm this high-significance tension, opening a potential window to new physics.

Key Words: large-scale structure of Universe – cosmology: observations – cosmology: theory – radio continuum: galaxies – infrared: galaxies – cosmic background radiation

Decoding the cosmic dipole with likelihood-based and likelihood-free inference

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Abstract

We outline our ongoing efforts to understand the cosmic dipole tension—the disagreement between the dipole amplitude of galaxy surveys and the Cosmic Microwave Background—using Bayesian techniques. As the community moves from traditional frequentist approaches (see e.g [1–2]) to full Bayesian treatments (see e.g. [3–5]), more scrutiny is being placed on how to consistently handle systematic effects. We outline historic approaches, which used techniques like nested sampling and classic MCMC with explicitly-defined likelihood functions. We also discuss the potential of Simulation-based Inference (SBI), including neural posterior and likelihood estimators, to resolve these systematics where a likelihood function cannot be defined. SBI could pave the way for robust measurements of the dipole which more thoroughly handle the subtleties of galaxy datasets.

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Key Words: Dipole, Cosmic; Inference, Simulation-based; Inference, Bayesian; Errors, Systematic

Unveiling Gravitational Lenses in Colour: A Bayesian Approach to Multi-band Inference

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Abstract

Strong gravitational lensing offers a unique window into the Universe: it enables the study of galaxy-scale mass distributions, magnified high-redshift sources, and cosmological parameters. As lens samples grow and imaging capabilities improve, these systems are becoming powerful astrophysical and cosmological probes. However, reconstructing gravitational lenses remains a fundamentally under-constrained and non-linear inverse problem. Bayesian inference provides a principled framework to explore degenerate parameter spaces while delivering robust uncertainty quantification.

I will present a Bayesian forward-modeling pipeline that jointly models four-band (z, i, r, g) imaging from PISCO for a sample of 16 strong lens candidates [1, 2]. For selected systems, I will also show reconstructions based on high-resolution HST data from the AGEL survey [3]. This work represents a step toward scalable, automated lens modeling in the era of high-volume, multi-band, and multi-resolution datasets.

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Key Words: Strong gravitational lensing, Bayesian inference, Multi-band imaging, MCMC

MODELING AFRICAN LION MOVEMENTS AND ECOLOGICAL CORRIDORS USING MAXENT AND GRID-BASED CLUSTERING

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Abstract

African lions (**Panthera leo**), often celebrated as symbols of strength and majesty, are facing escalating threats due to habitat fragmentation driven by agriculture, urban development, and human-wildlife conflict. This study aims to model lion movement patterns and identify ecological corridors that promote safe connectivity between fragmented habitats using presence-only data and MaxEnt modeling.

We began with a dataset of 6,638 lion presence records, featuring spatial and temporal attributes. To reduce noise and computational overhead, a grid-based clustering approach was implemented using ArcGIS Pro's Fishnet tool. Several grid sizes were tested, with 10,000×5,000 yielding the best spatial representation. Post-clustering, the dataset was condensed to 1,384 representative points.

Given the nature of presence-only data, the Maximum Entropy (MaxEnt) algorithm was chosen for species distribution modeling. Environmental predictors were derived from WorldClim's bioclimatic variables, specifically: BIO16 (Precipitation of the Wettest Quarter), BIO17, BIO18, and BIO19. Climate TIFF files were converted to ASC format using QGIS for compatibility with MaxEnt.

The model achieved an AUC score of 87%, indicating strong predictive performance. Results highlighted BIO16 as the most influential predictor of lion presence, with response curves revealing bell-shaped distributions—suggesting optimal precipitation thresholds for habitat suitability. Notably, the final prediction map identified both African and ecologically similar non-African zones suitable for lion survival.

This modeling framework provides an effective blueprint for identifying and preserving ecological corridors, aiding conservation strategies that aim to reduce human-wildlife conflict and safeguard African lion populations.

Key Words: African Lions, MaxEnt, Habitat Fragmentation, Species Distribution Modeling, Ecological Corridors, Grid-based Clustering, Precipitation Variables

PARAMETER LEARNING WITH PHYSICS-CONSISTENT GAUSSIAN PROCESSES

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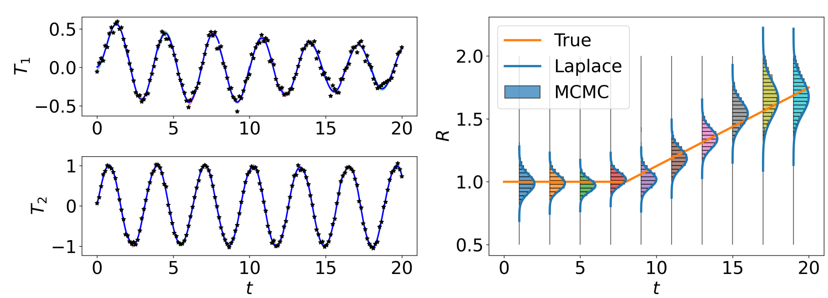
Abstract

Gaussian processes (GPs) constrained by linear differential operators have recently gained interest, but their full potential remains unexplored. We pick up the approach of [1] by parameterizing GPs via the null space of operators of partial or ordinary differential equations while including inhomogeneities and possibly non-constant coefficients. With this approach, physical parameters emerge as GP hyperparameters, enabling efficient learning of said parameters directly from data. We extend this framework by incorporating uncertainty quantification for the learned parameters, using optionally Laplace approximations for efficiency or MCMC-based posterior sampling. In addition, we introduce a pragmatic window approach that enables tracking changes in parameters over time. This makes the method particularly interesting for future industrial applications such as fault detection and -diagnosis, where identifying changes in interpretable physical parameters is critical. Compared to "standard" Bayesian parameter estimation, the method reduces manual effort: there is no need to solve the equations directly or define sampling grids for parameters, as the model relies on optimization. The approach is able to support multiple parameters and spatial dimensions, and our implementation is easily adaptable to new applications and equations.



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Prior Specification for Bayesian Model Averaging in Metabolic Flux Inference : A Dual Statistical–Computational Perspective

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Abstract

Metabolic network models are central in systems bio(techno)logy, capturing how substrates are converted into products, including the cellular components necessary for growth [1]. Metabolic network models are parameterized by biochemical reaction rates (fluxes). Quantitative understanding of the fluxes allows biotechnologists to develop new efficient bioprocesses and to assess the effects of drugs on human metabolism. Yet inferring fluxes using metabolic models is statistically challenging: data provide only limited information about the correct model structure, while the flux parameter spaces are high-dimensional and complex.

Here, the Bayesian framework is especially appealing as it allows accounting for all reasonable network models using Bayesian model averaging (BMA) [2]. BMA requires specifying priors for both network models and flux parameters. Despite BMA's acute prior sensitivity[3], the impact of model priors and flux priors on flux inference has not yet been studied. Studying prior choice in this context is statistically and computationally challenging because the priors for the model set and the priors for the flux parameters are entangled (each model structure induces a specific, nontrivial parameter space).

Here we introduce a dual statistical-computational perspective on prior specification in metabolic flux inference. Statistically, we quantitatively examine how prior choices influence model weights and flux posteriors under BMA. Computationally, we apply posterior repartitioning and show how carefully chosen priors accelerate trans-dimensional diffusive nested sampling [4] for metabolic networks without degrading flux inference quality. Together, these insights yield practical guidelines for prior selection, enabling more efficient and robust metabolic flux inference.

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Inference for multi-messenger gravitational wave lensing

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Abstract

Gravitational waves and gravitational lensing both arise as natural consequences of the theory of general relativity. As lensing bends the geodesics both gravitational waves and light travel on, it is only a natural extension of the theory to assume that gravitational waves can be lensed in the same way as light. Strong gravitational lensing has been a staple of EM studies since the first observation of a lensed quasar in 1979, and searches for gravitational wave lensing have been an ongoing, active effort of the LIGO-Virgo-KAGRA collaboration since 2019.

As the binaries from which gravitational waves originate should be hosted by bright galaxies, it has been proposed that the object that lenses the gravitational wave should identically lens the host galaxy and thus enable one to connect dark lensed binaries to their host galaxies [1, 2]. We present a Bayesian framework [3] which allows us to use real lensed gravitational wave data in combination with EM lens images for host identification and localization of the binary inside the source galaxy. This is achieved by integrating lensed gravitational wave analysis data products with existing lens modelling tools for a multi-messenger joint likelihood using Hamiltonian Monte Carlo sampling. We also present some proposed applications of this localization methodology and its results.

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Key Words: gravitational lensing, gravitational waves, multi-messenger

Bayesian Inference for loss hyperparameters in Generalised Bayesian Inference

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14/06/2025

Abstract

In Generalised Bayesian Inference (GBI [1-2]), the learning rate and hyperparameters of the loss must be estimated. However, these inference-hyperparameters can't be estimated jointly with the other parameters by giving them a prior, as we discuss. Several methods for estimating the learning rate have been given [3] which elicit and minimise a loss based on the goals of the overall inference (in our case, prediction of new data). However, in some settings there exists an unknown "true" learning rate about which it is meaningful to have prior belief. It is then possible to use Bayesian inference with held out data to get a posterior for the learning rate. In our arxiv paper [4], we give conditions under which this posterior concentrates on the optimal rate and suggest hyperparameter estimators derived from this posterior. The new framework supports joint estimation and uncertainty quatification for inference hyperparameters. Experiments show that the resulting GBI-posteriors out-perform Bayesian inference on simulated test data and select optimal or near optimal hyperparameter values in a large real problem of text analysis. Generalised Bayesian inference is particularly useful for combining multiple data sets and most of our examples belong to that setting. As a side note we give asymptotic results for some of the special "multi-modular" Generalised Bayes posteriors [5], which we use in our examples.

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Key Words: Generalised Bayes, Semi-Modular Inference, Learning Rate

Uncovering Activity Patterns in Free-Living Physical Activity Data from Wearable Devices via Bayesian motif-based Clustering method

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Unsupervised clustering of curves based on their shapes is a significant problem for diverse scientific applications. However, many functional clustering methods focus on amplitude differences, neglecting the considerable impact of phase variations, particularly in physical activity data. Analyzing the similarity between two activity curves necessitates considering phase and amplitude variations for meaningful insights. Moreover, research discussing or proposing methods for studying physical activity (PA) data through cluster analysis to identify activity patterns remains limited. Hence, we propose a novel approach leveraging elastic functional data analysis to compare activity curves. We introduce a Bayesian motif-based clustering method to uncover distinct activity patterns (motifs) within free-living PA data collected from wearable devices.

Initially, we segment the 24-hour activity curve into fixed-time intervals, using the fundamental time unit of an activity as the basis for segmentation. Subsequently, elastic shape analysis is employed for these activity segments, and elastic distance is utilized to quantify curve dissimilarity. This elastic-distance matrix is decomposed into phase and amplitude distance components, which are modeled using the Von Mises and Gamma distributions, respectively. Utilizing the Bayesian nonparametric clustering framework with a Dirichlet process, we derive cluster results and the posterior distribution, thereby inferring the posterior distribution of the number of clusters. Finally, these identified activity clusters could be used to define new digital biomarkers as PA features for further analysis.

This study aims to develop a novel Bayesian functional clustering methodology for activity pattern discovery, eliminating the necessity for pre-specifying the number of clusters. By employing a flexible prior on the space of data partitions and analyzing the resulting posterior distribution, our approach will effectively determine the optimal clustering configuration. Each cluster exhibits distinct characteristics, with some relying more on the amplitude distance component, while others are more dependent on the phase distance component. We validated the performance of our proposed method through real-world applications.

We hope this framework will provide a practical solution for real-world datasets in prospective applications. This method will facilitate data-driven partitioning within functional data analysis, thereby making a significant contribution to ongoing research, such as association studies, by enabling the discovery of meaningful patterns and relationships within health events. Moreover, it is hypothesized that the motifs identified through this method can serve as a foundational basis for the establishment of digital biomarkers, subsequently advancing research in the domain of physical activity analysis.

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Combinatorial Characterization of Exponential Families of Lumpable Stochastic Matrices

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Abstract

Exponential families of distributions arise naturally as solutions to maximum entropy problems, where the constraints are expressed as fixed expected values of certain statistics. This maximum entropy problem was extended in [1] to functions of two consecutive data points, leading to the recognition of the exponential family structure of transition matrices of Markov chains. An information geometric treatment of transition matrices of irreducible Markov chains—including their dually flat structure and a formal definition of exponential families—was later provided by Nagaoka in [2].

A Markov chain is called lumpable [3] if it can be aggregated into a simpler form by merging certain states, while still preserving the Markov property in the resulting process. It was shown in [4] that, in general, the set of lumpable Markov chains with respect to a given lumping function does not form an exponential family of transition matrices. In this work, we initiate the problem of characterizing exponential families of lumpable Markov chains with respect to a fixed lumping map, and we provide the first set of necessary and sufficient conditions for this characterization.

The full manuscript can be found in [5].

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Key Words: Information geometry; irreducible Markov chains; lumpability; exponential families

Visualizing causal pathways and quantifying marginal and interaction effects of risk factors on long-term Type 2 Diabetes development: A conditional survival Bayesian network approach.

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Over the past decade, traditional demographic, lifestyle, and metabolic factors—as well as air pollution—have been recognized as key contributors to Type 2 diabetes (T2D). However, their complex, interacting effects have seldom been characterized in long-term population studies.

In this analysis, we leveraged 11 years of follow-up data from the Korean Genome and Epidemiology Study (KoGES) Ansan cohort to explore causal pathways among demographic, metabolic, lifestyle, and environmental exposures leading to incident T2D. We employed a Conditional Survival Bayesian Network (CSBN), which integrates survival analysis with Bayesian network modeling to simultaneously estimate direct, indirect, and confounded effects while accommodating censored and incomplete data.

The CSBN's transparent probabilistic framework clearly delineated dependencies among risk factors and enabled intuitive visualization of their interplay. Interventional analysis quantified each factor's causal contribution to 11-year T2D incidence: obesity (38%), elevated alanine aminotransferase (ALT; 36%), family history of T2D (30%), high sulfur dioxide (SO2) exposure (29%), smoking (29%), and older age (28%). We also identified several variables—hypertension, alcohol consumption, income, partnership status, aspartate aminotransferase (AST), and PM2.5—that demonstrated significant effects only in the absence of confounders, implying that their impacts may be obscured in fully adjusted models. Furthermore, the CSBN uncovered synergistic interactions, notably between obesity and SO2 exposure, which conventional survival approaches might overlook.

These findings underscore the importance of integrated public health strategies targeting multiple, interacting risk factors—including environmental pollutants—to curb the rising burden of T2D.

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FAST BAYESIAN MODEL COMPARISON ACROSS MULTIPLE PRIORS AND DATASETS

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Abstract

Model comparison is central to scientific inference, providing a principled way to evaluate competing hypotheses. In the Bayesian framework, this involves computing the marginal likelihood, or Bayesian evidence. It is often desirable to explore a grid of plausible modelling choices, requiring full (Markov chain) Monte Carlo simulations for each variant, which is computationally burdensome. We present two novel methods to significantly reduce this computational cost by exploiting the recently developed learned harmonic mean estimator for Bayesian evidence computation [1,2], which is agnostic to posterior sampling strategy and hence allows flexible computational schemes. Our first method enables prior sensitivity analysis of the Bayesian evidence with minimal additional cost. This is particularly valuable when it is difficult to derive principled or physically motivated priors. The method works by recomputing the evidence after re-weighting posterior samples from the original prior, requiring only minutes and avoiding additional sampling runs. Our second method efficiently computes joint posteriors and Bayesian evidences across multiple independent datasets using only posterior samples from individual datasets. While previous approaches either obtain fast joint posteriors without evidences [3,4], or require additional nested sampling runs to get the evidence [5], our method computes both joint posteriors and evidences using arbitrary sampling schemes which can be optimised for computational efficiency. We demonstrate the effectiveness of our approach on a cosmological joint analysis combining DESI, CMB, and supernovae data across a grid of 12 model/dataset combinations [7], achieving up to 18x speedup compared to traditional approaches at no cost to accuracy, with potential for more as the number of data combinations increases.

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Key Words: Bayesian model comparison, machine learning, cosmology

A new lens on gravitational lens modelling

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Abstract

The most well-accepted cosmological model, ΛCDM, is named after two components (Λ, a cosmological constant description of dark energy; CDM, cold dark matter) that have never been observed in a laboratory. Fortunately, reconstructions of galaxy–galaxy strong gravitational lensing data – wherein we observe a higher–redshift galaxy magnified and multiply–imaged by a lower–redshift galaxy – are sensitive to the nature of both of these elusive substances, and offer competitive opportunities to understand their physics. More fortunately, the scarcity of gravitational lensing data is anticipated to become a non–issue in the coming years. Euclid, in its infancy, has already ∼doubled the number of lens candidates [1], and in combination with the Vera Rubin Observatory is anticipated to multiply our sample $\sim 10^4$–fold [2].

The next challenge to overcome is accurately modelling this data to extract cosmological information. I will put forth a promising new approach to reconstructing high resolution galaxy–galaxy lensing data, by fully forward modelling the background source and foreground lens on a GPU, within a robust Bayesian framework employing variational inference and Hamiltonian Monte Carlo sampling. As a case study, I will highlight one of the most comprehensively studied, precision cosmology–grade examples of a known lens – SDSS J0946+1006 – and discuss recent and ongoing efforts to constrain the nature of Λ and CDM with this system by wielding such techniques [3, 4].

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Key Words: Gravitational lensing, dark energy, dark matter, variational inference, Hamiltonian Monte Carlo

HIGH-DIMENSIONAL BAYESIAN INFERENCE IN COSMOLOGY THROUGH DIFFERENTIABLE SPHERICAL SIMULATIONS

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Abstract

The next generation of cosmological surveys promises unprecedented fidelity in mapping our universe. Field-level inference is uniquely positioned to extract information from such high-fidelity data but faces challenges due to its inherently high-dimensional nature. This becomes particularly demanding for analyzing wide-field spherical sky data from upcoming surveys, where computational expense poses significant hurdles. Recent advances in machine learning offer scalable solutions by integrating differentiable and probabilistic methods with efficient Monte Carlo techniques.

Recent work has demonstrated the effectiveness of field-level inference using either Bayesian hierarchical models (BHMs; Tsaprazi et al. 2022, Porqueres et al. 2022, Andrews et al. 2023, Lanzieri et al. 2024, Zeghal et al. 2024) or simulation-based inference (SBI; Lemos et al. 2023, Gatti et al. 2024, Jeffrey et al. 2024). These approaches have been complemented by advancements in Bayesian model selection with the use of the learned harmonic mean estimator (McEwen et al. 2021, Spurio Mancini et al. 2022, Polanska et al. 2023, Polanska et al. 2024a, Spurio Mancini et al. 2024) and the Savage-Dickey density ratio with normalizing flows (Lin et al. 2025) to provide a method of calculating the Bayes factor decoupled from the choice of sampler. Together, these methods enable efficient Bayesian model selection in high-dimensional settings.

In this work, we present a novel differentiable spherical simulation pipeline designed to address the challenges of field-level inference. Our approach combines an emulator for rapid initial condition solving, differentiable generators, and spherical compression techniques. By leveraging modern machine learning methodologies, we develop scalable solutions for high-dimensional inverse problems in cosmology, facilitating both BHM sampling and SBI applications.

Key Words: spherical simulations, differentiability, field-level inference, cosmology

A Methodological Framework for Constructing Digital Biomarkers via Functional Principal Component Analysis of High-Dimensional Functional Activity Data

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The proliferation of wearable devices allows for continuously collecting high-resolution behavioral data, such as daily physical activity, in naturalistic settings. These data, often represented in functional form, offer new opportunities for digital health. However, a key challenge remains in extracting discriminative features from high-dimensional and structurally complex data to construct clinically applicable and meaningful digital biomarkers.

This study proposes a methodological framework using Functional Principal Component Analysis (FPCA) to construct an interpretable and generalizable digital biomarker from daily activity data. The framework extracts dominant modes of variation (functional principal components) from raw activity functions. Following the extraction of FPCs, we constructed a test statistic based on a similarity measure to compare differences in both eigenfunctions and FPC scores between the case and control groups. This process generates low-dimensional features that characterize individual activity patterns, enabling group-level difference testing and classification modeling.

We applied this framework to two clinical datasets: individuals with mood disorders and another with attention-deficit/hyperactivity disorder (ADHD), each compared with healthy controls. While the primary daily activity rhythms were broadly similar across all groups, the FPCA-derived features successfully captured subtle but significant group differences. Specifically, individuals with ADHD displayed more pronounced differences from controls. A contextual analysis comparing weekday and weekend patterns revealed further distinctions: controls exhibited delayed activity peaks on weekends, whereas participants with mood disorders showed earlier and slightly more intense peaks.

In conclusion, FPCA is a practical methodology for constructing digital biomarkers from dense time-series data. This approach captures subtle yet clinically meaningful behavioral variations by distilling high-dimensional functional data into interpretable, low-dimensional features. This framework demonstrates strong potential for enhancing personalized health assessment and remote behavioral monitoring tools.

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Bayesian Stability Selection

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Abstract

Stability selection is a general framework for structure estimation and variable selection in high-dimensional settings, where the number of variables substantially exceeds the number of observations. Stability selection is primarily grounded in frequentist principles. In this presentation, we propose an enhanced methodology that integrates Bayesian analysis to refine the inference of selection probabilities within the stability selection framework. Traditional approaches rely on selection frequencies for variable selection, often disregarding domain-specific knowledge. Our methodology incorporates prior information to derive posterior distributions of selection probabilities, thereby enhancing inference and, often, improving selection stability by reducing the variance of selection probabilities. The use of the Beta-Binomial framework for modelling the prior-likelihood structure is well-established in the Bayesian variable selection literature. We provide a brief review of existing approaches for specifying the parameters of the prior distribution and propose a new two-step procedure to elicit prior information and regulate its influence on the final selection results. In addition, using posterior distributions, we offer Bayesian credible intervals to quantify uncertainty in the variable selection process. Our approach preserves the versatility of the stability selection framework and is suitable for a broad range of structure estimation challenges, including gene expression profile analysis.

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Key Words: Bioinformatics, Bayesian Analysis, Feature Selection, Prior Elicitation, Structure Estimation, Variable Selection

Information Content and Maximum Entropy Reconstruction in Stellar Surface Mapping Inverse Problems
44th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering

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Detailed observations of solar surface features have provided fundamental insights into stellar physics, including magnetic dynamos, differential rotation, activity cycles, and transient events such as coronal mass ejections and solar flares. However, nearly all other stars remain unresolved, making inference of their surface features a challenging inverse problem: reconstructing spatial distributions from temporally-varying, spatially-integrated observational data. Traditional photometric light curve inversion methods suffer from severe degeneracies, with maximum entropy reconstructions limited to recovering information only for low-order spherical harmonic modes due to insufficient constraining information. These degeneracies can only be partially mitigated through highly restrictive—and sometimes unphysical—prior assumptions. We demonstrate that high-precision astrometric measurements can recover more spherical harmonic modes than photometric techniques, effectively breaking degeneracies inherent to traditional methods. The astrometric approach yields enhanced spatial resolution while remaining complementary to existing photometric approaches. Information-theoretic analysis using Fisher matrices confirms the superior performance of astrometric measurements and quantifies the fundamental limits of each observational modality. Combining astrometric and photometric data reduces uncertainties in stellar surface reconstruction, enabling more detailed understanding of unresolved stellar surfaces.

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A Hierarchical Bayesian Extension of Dynamic Causal Modelling for Evolving Neural Systems

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Abstract

Dynamic Causal Modelling (DCM) is a Bayesian framework for inferring effective connectivity among brain regions from fMRI data, integrating neuronal state equations with a hemodynamic observation model to link latent neural dynamics to observed BOLD responses. Classical DCM, pioneered by Friston and colleagues, has been highly influential in systems neuroscience, but its assumptions of deterministic, time-invariant dynamics and empirical Gaussian priors constrain its ability to capture heterogeneity across individuals and the nonstationary nature of brain connectivity. In this work, we propose a hierarchical Bayesian extension of DCM that unifies the interpretability of Friston-style models with the flexibility of stochastic formulations. Our framework incorporates three innovations: (i) hierarchical modelling of subject-specific connectivity to account for inter-individual variability while borrowing strength across the group, (ii) age-dependent group-level effects that allow developmental and lifespan trajectories of connectivity to be explicitly modelled, and (iii) time-varying effective connectivity embedded in a stochastic state-space representation to characterize evolving causal interactions. This formulation enhances robustness, generalizability, and biological realism, enabling richer inference on neural systems. We demonstrate the utility of the approach through simulation studies and outline its potential for application to large-scale neuroimaging cohorts where heterogeneity and temporal dynamics are critical.

Keywords: Effective connectivity, Dynamic Causal Modelling (DCM), Bayesian hierarchical modelling, Time-varying connectivity

BAYESIAN MODEL COMPARISON OF BASIS FUNCTION SYSTEMS FOR PARTICLE-REFLECTION-DISTRIBUTION DATA

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Abstract

Numerical simulations for particles impinging on the first wall of fusion devices yield angle- and energy-distributions of reflected particles. Common practice is to summarize this data in extensive tables for input to plasma wall interaction codes. Our approach is to summarize the multi-variate distributions by a suitable basis function system and reduce the amount of data to be stored to the coefficients of the function system under consideration. In this paper we employ MCMC within a Bayesian model comparison for calculating the evidence in order to determine which of a selection of hemispherical basis function systems performs best.

Key Words: Bayesian model comparison, hemispherical basis function systems, particle reflection distribution data

MOMENT-GENERATING FUNCTION METHODS IN BAYESIAN INFERENCE

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Abstract

We present a new analytical method to derive a likelihood function that is marginalised over a population of parameters. This method can be used for computational advantage in the context of Bayesian hierarchical models, marginal likelihood calculations in Bayesian models and in random-effect linear mixed-effects models. The key innovation is the specification of necessary integrals in terms of high-order (sometimes fractional) derivatives of the prior moment-generating function, if particular existence and differentiability conditions hold.

We confine our attention to Poisson and gamma likelihood functions. Under Poisson likelihoods, the observed Poisson count determines the order of the derivative. Under gamma likelihoods, the shape parameter, which is assumed to be known, determines the order of the fractional derivative.

We also present some examples validating this new analytical method, including an astrostatistics example on counting X-ray photons.

Key Words: Poisson likelihoods, gamma likelihoods, fractional derivatives, marginal likelihoods, posterior moments, generating functions

IMPROVED MAGNETIC EQUILIBRIUM RECONSTRUCTION AND DIAGNOSTIC OPTIMIZATION USING BAYESIAN METHODS ON THE WEST TOKAMAK

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Abstract

Next-generation fusion devices based on magnetic confinement of a hot plasma present significant challenges in obtaining reliable information about the plasma state in real time. On the one hand, measurements from diagnostics are limited due to spatial and cost constraints. On the other hand, model-based predictions have limitations due to model uncertainty and computational restrictions. Therefore, it is essential to merge information from multiple sources, at the same time taking into account uncertainty propagation. Bayesian methods offer a principled way to address these issues, while leaving room for optimization of diagnostic design parameters by minimizing the uncertainty on the inferred plasma state.

In this work, we address estimation of the magnetic configuration of the plasma, which is crucial for real-time plasma control and, ultimately, for safe operation of the machine. Our approach is based on current tomography, relying solely on external magnetic measurements. The method is validated on the WEST tokamak, based on a prior current tomogram derived from a set of reference WEST equilibria. Currents in conducting structures outside the plasma are also taken into account, using a separate Gaussian process prior. We demonstrate the method's ability to reduce systematic errors in the reconstruction process. Furthermore, we apply Bayesian experimental design to optimize the design parameters of the magnetic sensors. In particular, we show that the number of sensors can be reduced considerably, without compromising the accuracy of key derived quantities. This confirms the possibility to reduce systematic errors, at the same time respecting space and cost constraints in future devices.

References:

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HIGH-DIMENSIONAL UNCERTAINTY QUANTIFICATION WITH DEEP DATA-DRIVEN PRIORS

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Abstract

Many inverse problems exhibit high-dimensional parameter spaces and highly computational demanding forward operators. A case in point is imaging the raw observations made by radio interferometric telescopes, such as the Square Kilometre Array (SKA), where one seeks to recover high resolution images of the sky from huge data volumes and with highly accurate forward operators modelling the telescope, resulting in extremely challenging computational problems that approach the exascale. Many inverse problems are often ill-posed and ill-conditioned and so to effectively solve them regularising prior information is typically injected. Deep data-driven priors, often encoded in neural networks, provide more expressive priors than classical hand-crafted priors and have led to significant improvements in reconstruction fidelity. Nevertheless, in both settings it is critical to quantify uncertainties, which is often neglected in highly computationally demanding scenarios when it is not feasible to explore the full posterior distribution. I will discuss a number of strategies for quantifying uncertainties in computationally demanding high-dimensional inverse imaging problems regularised by deep data-driven priors, which leverage concepts of convexity (Liaudat *et al.* 2024), regularisation (Whitney *et al.* 2024, Bendel *et al.* 2023, Mars *et al.* in prep.), symmetry (Tachella & Pereyra 2023), and conformal prediction (Angelopoulos *et al.* 2022, Everink *et al.* 2025).

aim-resolve: Automatic Identification and Modeling for Bayesian Radio Interferometric Imaging

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Abstract

Modern radio interferometers deliver large volumes of data containing high-sensitivity sky maps over wide fields-of-view. These large area observations can contain various and superposed structures such as filaments, point sources, extended objects, and diffuse background emission. To fully realize the potential of these observations, it is crucial to build appropriate sky models which reconstruct and separate the underlying astrophysical components. In this work, we introduce `aim-resolve`, an automatic and iterative method that combines the Bayesian imaging algorithm `resolve` with deep learning and clustering algorithms to detect and model different astrophysical components in radio observations while providing uncertainty quantification of the results. By using different model descriptions for point sources, extended objects, and background emission, the method efficiently separates the individual components and improves the overall reconstruction of the data. We demonstrate the effectiveness of this method on synthetic image data and apply it to an L-band (856 - 1712 MHz) MeerKAT observation of the radio galaxy ESO 137-006 and other radio galaxies in that environment. We further show an extension of the multi-component sky model to handle multi-frequency data and to model the spectral behavior of the different astrophysical components, which can give insights into the evolution of radio-emitting plasmas in the imaged galaxies.

Key Words: Bayesian inference – radio astronomy – machine learning

BAYESIAN MULTI-FREQUENCY STRONG LENSING

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Abstract

Strong gravitational lensing presents a challenging inverse problem requiring simultaneous reconstruction of source brightness and lens mass distributions from noisy, distorted observations. We present LensCharm, a novel Bayesian framework that addresses this ill-posed problem through a generative modeling approach, naturally encoding physical constraints such as flux and mass positivity.

Our method achieves full flexibility in modeling the underlying physical fields by combining parametric models for global structure with non-parametric Gaussian process priors for complex morphologies. The key innovation lies in our joint posterior formulation that couples source and lens parameters, enabling proper uncertainty propagation between these inherently correlated quantities while avoiding the restrictive assumptions of traditional parametric approaches.

We extend the original single-frequency formulation to multi-frequency observations, dramatically increasing both the dimensionality and computational complexity of the inference problem. To tackle the resulting high-dimensional posterior, we employ Variational Inference, which transform the challenging sampling problem into efficient optimization while maintaining accurate uncertainty quantification. The computational demands are addressed through a JAX implementation that leverages GPU acceleration, achieving orders-of-magnitude speedups essential for practical application.

This multi-frequency extension introduces frequency-dependent correlations requiring careful treatment of the joint likelihood across data channels. However, these additional observational constraints significantly enhance our ability to detect dark matter substructure, including low-mass halos previously inaccessible to single-frequency analyses.

Our open-source implementation demonstrates how modern Bayesian computation—combining variational inference, automatic differentiation, and GPU acceleration—can tackle complex, high-dimensional inverse problems.