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# PREFACE

For many decades, Bayesian statistics—with its impeccable foundation but demanding computational challenges—and machine learning—with its vast repertoire of effective methods and quick computational strategies—operated largely in isolation. In modern times, however, breakthrough computational methods have enriched the Bayesian paradigm, while connections of various machine learning approaches to Bayesian principles have become topics of fervent investigation. Indeed, the intersection of Bayesian statistics and machine learning represents one of the most vibrant and consequential frontiers in modern data science. This special issue of *Statistics and Applications* brings together a remarkable collection of invited papers to celebrate this grand confluence, showcasing methodological and computational innovations that span the full spectrum from fundamental theory to practical implementation across both paradigms.

The eight papers assembled here address challenges that lie at the heart of contemporary Bayesian statistics and machine learning, while also offering a glimpse into the future. The topics range from general function optimization theory, powered by Bayesian sophistication and versatility, to handling intricate spatio-temporal dependence structures including Bayesian feature extraction; from unraveling the mysteries of Hamiltonian Monte Carlo—the robust computational engine driving much of Bayesian computation—to Bayesian variable selection in streaming data; from amortized Bayesian inference with neural architectures, offering a magical blend between the two paradigms, to a new technique for AI explainability; from survey-weighted Bayesian logistic regression to the futuristic world of quantum computation and the esoteric elegance and power of quantum Markov Chain Monte Carlo.

We begin this volume with Roy and Bhattacharya's "Function Optimization with Posterior Gaussian Derivative Process," which proposes a Bayesian optimization algorithm that leverages derivative information to achieve almost sure convergence to true optima. The method demonstrates substantially greater accuracy than conventional approaches including Fisher scoring, BFGS, and simulated annealing, across problems ranging from one to one hundred dimensions.

Spatial and temporal dependence structures are addressed by two complementary papers. Olayinka and Nandram, in "Bayesian Predictive Inference for Multiple Series with Correlated Spatial Priors on Autoregressive Parameters," develop a panel data framework with conditional autoregressive priors that borrow information across neighboring geographical areas, achieving median RMSE reductions of over 30% relative to non-spatial benchmarks. Frady, Dey, and Mohammed, in "Bayesian Feature Extraction using Gaussian and Diffused-gamma Priors for High Dimensional Spatio-Temporal Data," present a two-stage feature extraction procedure combining FDR-controlled screening with spatial-temporal clustering, applied successfully to EEG data for identifying brain regions associated with chronic alcohol exposure.

The computational engine of modern Bayesian inference is the focus of Mukherjee and Vats's "Hamiltonian Monte Carlo for (Physics) Dummies," a pedagogical review that demystifies HMC for researchers without physics backgrounds by framing it within the Metropolis-Hastings-Green algorithm and elucidating its physical intuition through running examples.

Model selection receives timely attention in Ghosh's "On the Choice of Model Space Priors and Multiplicity Control in Bayesian Variable Selection," which compares priors from discrete uniform through Beta-Binomial to the Matryoshka Doll prior in streaming logistic regression, revealing that no single prior dominates across all scenarios.

The amortization of Bayesian inference through neural networks is explored by Shreshth, Hazra, and Mukherjee in "Neural Architectures for Amortized Bayesian Inference," which examines feedforward networks, Deep Sets, and Transformers as adaptive basis expansions, neural generalizations of the method of moments, and learned kernel smoothers respectively, characterizing their sample efficiency and capacity trade-offs.

Yang and Nandram tackle survey-weighted inference in "Bayesian Predictive Inference in Logistic Regression with Covariates and Survey Weights," systematically comparing six models with original, trimmed, and calibrated weights, demonstrating that normalized densities with trimmed weights perform best in the presence of outliers.

Finally, Dhamapurkar and Das's "From Classical Probability to Quantum Amplitudes" provides a self-contained pedagogical bridge from Kolmogorov's axioms to quantum analogues of conditional probability, Bayes' rule, expectation, and maximum likelihood. Through the running example of estimating a coin's bias, the paper explains Grover's search, Quantum Amplitude Estimation, the HHL algorithm, and Quantum Markov Chain Monte Carlo, while honestly addressing the practical bottlenecks of data loading and readout that determine when quantum speedups translate into real-world advantage.

Taken together, these papers illustrate the remarkable breadth and depth of contemporary Bayesian and machine learning research. They demonstrate that the Bayesian paradigm does not rest on its lofty ideals to the exclusion of other frameworks; rather, it embraces the strengths of modern-day machine learning to launch a two-pronged attack on problems often regarded as insurmountable in the past. The key themes that emerge across the collection—the importance of structured prior specification, the power of hierarchical modeling, the necessity of computational innovation with an eye to the future, embedding deterministic functions and machine learning approaches in broad Bayesian frameworks, and the value of theoretical guarantees—testify to the enduring relevance of Bayesian thinking in collaboration with machine learning toward reaching the zenith of AI.

We are particularly pleased that this special issue reflects the global nature of the Bayesian and machine learning community, with contributions from researchers based in India, the United States, and perhaps beyond. The diversity of perspectives and approaches represented here is a testament to the vitality of Bayesian wisdom in combination with the machine learning enterprise as an international intellectual endeavor.

We extend our deepest gratitude to the authors for their outstanding contributions, to the reviewers for their careful and constructive evaluations, and to the editorial team of *Statistics and Applications* for their support in bringing this project to fruition. We hope that this collection will serve as both a valuable reference for researchers and an inspiration for future work at the intersection of Bayesian statistics and machine learning.

As the field continues to evolve—driven by new data sources, new computational capabilities, and new scientific questions—the principles and methods showcased in this volume will undoubtedly play a central role. The papers collected here represent not only the state of the art but also signposts for the directions in which our field is heading. We invite readers to engage with these contributions, to build upon them, and to join in the ongoing endeavor to develop statistical methods that are at once principled, powerful, and practical, carrying forward to generations yet to arrive.

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