ASU School of Mathematical and Statistical Sciences
Arizona State University

M E M O R A N D U M

DATE: 10/06/2023

TO: Faculty and Students

FROM: Professor(s) Douglas Cochran Shiwei Lan
Chair/Co-Chairs of Keenan Eikenberry
Defense for the PhD in Applied Mathematics
Committee Members

Babak Shahbaba
Gautam Dasarathy
Brett Kotschwar

DEFENSE ANNOUNCEMENT

Candidate: Keenan Eikenberry

Defense Date: October 25, 2023

Defense Time: 1:00 PM

Virtual Meeting Link: https://asu.zoom.us/j/84656951284 Attend Live: Wexler Hall (Tempe) WXLR 206

Title: Bayesian Inference for Markov Kernels Valued in Wasserstein Spaces

Please share this information with colleagues and other students, especially those studying in similar fields. Faculty and students are encouraged to attend. The defending candidate will give a 40 minute talk, after which the committee members will ask questions. There may be time for questions from those in attendance. But, guests are primarily invited to attend as observers and will be excused when the committee begins its deliberations or if the committee wishes to question the candidate privately.

ABSTRACT
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Bayesian Inference for Markov Kernels Valued in Wasserstein Spaces

ABSTRACT

In this work, the author analyzes quantitative and structural aspects of Bayesian inference using Markov kernels, Wasserstein metrics, and Kantorovich monads. In particular, the author shows the following main results: first, that Markov kernels can be viewed as Borel measurable maps with values in a Wasserstein space; second, that the Disintegration Theorem can be interpreted as a literal equality of integrals using an original theory of integration for Markov kernels; third, that the Kantorovich monad can be defined for Wasserstein metrics of any order; and finally, that, under certain assumptions, a generalized Bayes's Law for Markov kernels provably leads to convergence of the expected posterior distribution in the Wasserstein metric to an optimal value. These contributions provide a basis for studying further convergence, approximation, and stability properties of Bayesian inverse maps and inference processes using a unified theoretical framework that bridges between statistical inference, machine learning, and probabilistic programming semantics.