Publications

1 With referees

   Introduces a new Bayesian test that computes support in the data towards the null hypothesis that the state space pdf that the available data is sampled from is an isotropic function, where in lieu of the assumption of isotropy, the likelihood is rendered intractable.

   We develop a new fast method for the dichotomisation of a (large) test score data, using which, we then compute the uncertainty in the measurements (of examinee ability) that the data comprises, as parametrised by the error variance of the test. We implement this to compute the classically defined reliability (i.e. complement of uncertainty) of the test, and estimate the true scores of any given examinee.

2 Journal papers: in preparation

1. Sofia Massa, Kangrui Wang & Dalia Chakrabarty “MCMC-based Inference on Graphical Models of Large Multivariate Data Sets, and Testing for Independence of such Data-sets by Finding Distance Between the Graphs”.
   We develop a method for making MCMC-based inference on the graph given each of two multivariate data sets, (without resorting to conjugacy), where the two data sets are realised at different experimental conditions, to then compute the Hellinger distance between them to identify independence of the data sets. Application to the data sets of a number of different attributes of a sample of 1000 Portuguese white and red wines is undertaken.

2. Kangrui Wang & Dalia Chakrabarty, “Bayesian Covariance Modelling of Large Tensor-Variate Data Sets & Inverse Non-parametric Learning of the Unknown Model Parameter Vector”.
   We develop a new method for supervised learning of a tensor-variate functional relationship between an unknown model parameter vector and a tensor-shaped data using high-dimensional Gaussian Processes, leading to Bayesian inverse learning of the unknown model parameter given the test data. Application to econometric data is undertaken.

   Discusses a new unsupervised learning methodology in which the unknown model parameter vector is embedded within the support of the state space density; model checking is undertaken.

4. Dalia Chakrabarty et al., “Inference on galaxy mass density functions under constraint on integrated mass”, 2015, paper that builds on Bayesian “fusion learning” with applications to astronomy.

3 Publications in Journals and Peer-reviewed Conference Proceedings

   This paper includes the development of a new high-dimensional Gaussian Process that is used
to model the high-dimensional functional relationship between the unknown model parameter vector and a matrix-variate data. Model checking is discussed.

2. Chakrabarty, Dalia et. al, “Bayesian Density Estimation via Multiple Sequential Inversions of 2-D Images with Application in Electron Microscopy”, Technometrics, 57, 2, pg. 217–233. This paper includes the development of a novel Bayesian inverse unsupervised learning methodology, to perform multiple inversions of image data to learn unknown functions, using new priors developed on sparsity, and distinct models classed by the resolution of the available data.

3. S. Banerjee, A. Basu, S. Bhattacharya, S. Bose, Dalia Chakrabarty, and S.S. Mukherjee, “Minimum Distance Estimation of Milky Way Model Parameters and Related Inference”, 2015, SIAM/ASA Jl. of Uncertainty Quantification, 3, 1, pg. 91–115. We compute distance (Hellinger metric) between the bivariate density function estimated using real data and the density estimated using training data that is generated at chosen values of the unknown model parameter vector. Parameter value corresponding to closest match is identified, along with uncertainties.


followed by effect of smoothing functions - to estimate gravitational mass in distant galaxies, treated as highly under-abundant systems.


