Abstract

This thesis specifically aims at investigating a non-homogeneous Gaussian hidden Markov model (NHGHMM) under both univariate and multivariate settings. The model is known to be able to capture non-homogeneity of transition probabilities between the hidden states. This advantage for the model can provide more flexibility on a predictive ability in statistical inference.

A Bayesian approach was implemented for parameter estimation by proposing several advanced Markov chain Monte Carlo (MCMC) algorithms to contribute to an estimation aspect of the models. From a Bayesian perspective, the current literature on multivariate extensions of an NHGHMM is scarce.

In terms of efficiency and convergence, I discovered that the three proposed MCMC algorithms, the *adaptive Metropolis*, *symmetric delayed rejection adaptive Metropolis*, and *multiple-try adaptive Metropolis* algorithms, were more efficient and achieved faster convergence than the standard Metropolis-Hastings algorithm under the univariate setting. For performances of parameter estimation, those three MCMC algorithms were able to provide more reliable estimates compared to the conventional methods. In addition, a case study was conducted by using the multiple-try adaptive Metropolis algorithm, which was the most efficient MCMC algorithm amongst the three algorithms.

Likewise, the three proposed MCMC algorithms were more efficient compared to the standard Metropolis-Hastings algorithm through the simulation studies within the multivariate setting. For this particular simulation study, those proposed algorithms achieved satisfactory convergence in the same number of iterations. In terms of performances of parameter estimation, those three proposed algorithms generated reliable estimates. Overall, the case studies were mainly satisfactory, but one of them left a conundrum where the MCMC convergence was unachievable, creating a limitation with the model.

The methodologies for such models have not been fully explored in the literature, and thus, my original contributions are comprised of the proposed MCMC algorithms and a research contribution to the multivariate NHGHMMs. A set of R© and C++ code was specifically written to validate the proposed MCMC algorithms through the extensive simulation studies which were conducted in this thesis, making up part of my original contributions.