

## Abstract

Due to a demand for reliable methods for exploring intractable probability distributions, the popularity of Markov chain Monte Carlo techniques continues to grow. In the current age of Big Data, a lot of progresses depend on the analyses of large scale of data sets which introduce a new set of problems as it is often computationally expensive to apply standard MCMC algorithms to them. In this dissertation, we started with the theory and implementation of the Metropolis-Hastings algorithm, which is already widely used nowadays. Then, we introduced the Langevin dynamics in the form of Metropolis Adjusted Langevin algorithm. These algorithms do work wonderfully, but they are computationally expensive as one has to consider the whole data set to move to the next state. Therefore we introduced the recently proposed Stochastic Gradient Langevin Dynamics algorithm which is the integration of the stochastic optimization techniques with the Langevin dynamics. It is a very powerful algorithm that does not have the same problems as this algorithm skips the accept-reject step and only considers a subset of the full data set in order to propose a new state for the Markov chain. At the end of this report, we investigated the effect of the step sizes and the subset size of the Stochastic Gradient Langevin dynamics algorithm on the posterior sampling.