Methods for Accurate and Efficient Bayesian Analysis of Time Series

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Chapter 6

Summaries

6.1 English summary

This thesis investigates Bayesian inference over time series models with the emphasis put on applications in economics and finance. We adopt simulation-based techniques which are necessary in any nontrivial problem in this setting. The main motivation behind the presented research is to increase the efficiency and accuracy of these computationally intensive methods in several different contexts. One of the main topics addressed is efficient and precise risk estimation, or rare event analysis. Another problem studied in this thesis is the efficiency of various sampling algorithms, in particular importance sampling (IS) and Markov chain Monte Carlo (MCMC) algorithms. Finally, we address the issue of forecasting, from a single model as well as from a combination of models.

In Chapter 2 we present an accurate and efficient method for Bayesian estimation of two financial risk measures, Value-at-Risk and Expected Shortfall, for a given volatility model. We obtain precise forecasts of the tail of the distribution of returns not only for the 10-days-ahead horizon required by the Basel Committee but even for long horizons, like one-month or one-year ahead. The key insight behind our proposed IS based approach is the sequential construction of marginal and conditional importance densities for consecutive periods. By oversampling the extremely negative scenarios and giving them lower importance weights, we achieve a much higher precision in characterising the properties of the left tail.

In Chapter 3 we introduce a novel approach to inference for a specific region of the predictive distribution. An important domain of application is accurate prediction of financial risk measures, where the area of interest is the left tail of the predictive density of logreturns. Our proposed approach originates from the Bayesian approach to parameter estimation and time series forecasting, however it is robust in the sense that it provides a more accurate estimation of the predictive density in the region of interest in case of misspecification. The main contribution of this chapter is the novel concept of the partially censored posterior, where the set of model parameters is partitioned into two subsets: for the first subset of parameters we consider the standard marginal posterior, for the second subset of parameters (that are particularly related to the region of interest) we consider the conditional censored posterior. This approach yields more precise parameter estimation than a fully censored posterior for all parameters, and has more focus on the region of interest than a standard Bayesian approach.

In Chapter 4 we develop a novel efficient model-fitting algorithm for state space models. This flexible class of models is challenging due to their substantially more complicated fitting to data as the associated likelihood is typically analytically intractable. For the general case a Bayesian data augmentation approach is often employed, however, standard "vanilla" updating MCMC algorithms may perform very poorly in that case. This it due to high correlation between the imputed states and/or parameters and leads to the need for specialist algorithms. A Semi-Complete Data Augmentation algorithm circumvents the inefficiencies of the previous approaches by combining data augmentation with numerical integration in a Bayesian hybrid approach. This approach permits the use of standard "vanilla" updating algorithms that perform considerably better than the traditional approach in terms of considerably improved mixing and hence lower autocorrelation.

In Chapter 5 we propose a novel dynamic asset allocation approach in which model-based forecasts are directly combined with a set of data driven portfolio strategies, without the necessity to define a utility or other scoring function. The resulting dynamic asset-allocation model is specified as a combination of return distributions stemming from multiple pairs of models and strategies. The combination weights are defined through feedback mechanisms that enable learning, to allow for cross-correlation and correlation over time. To increase the efficiency and robustness of the simulations we introduce a new nonlinear filter based on mixtures of Student's t distributions. Diagnostic analysis of posterior residuals gives insight into the model and strategy incompleteness or misspecification.