CHAPTER VII

ANALYSIS OF POSTERIOR AND PRIOR DISTRIBUTION

Section I - Introduction: The talk first is about a comparison of Bayesian Model Selection based on MCMC with an application to GARCH-Type Models. The Bayesian inference became very popular in the last decade of the previous century. Scientists got both: methodology and computer power to perform realistic Bayesian data analysis. The difference between the classical and the Bayesian approach to statistics is a fundamental change of paradigm. In the classical analysis, it is assumed that we know the correct structure of the model, and want to estimate the ”true value” of the model parameters which are also assumed to exist. From a Bayesian point of view, there is no such thing as a true parameter value. All one has is a fixed collection of data.

Furthermore, one may have some prior idea about what value of the parameters could be expected, summarized in a (possibly non-or little informative) prior density of the parameters. Combining the prior density with the likelihood of observing the data a posterior density of the parameters is constructed. This posterior density is a quantitative, probabilistic description of the knowledge about the parameters in the model. The strong advantage of a Bayesian analysis is that the complete posterior distribution of the parameters can be used for further analysis: to create a prediction or to make a model selection. First the analyses of previous works were concerned with Metropolis-Hastings (MH) algorithm, GARCH-type model, and MCMC simulations.
7.1.1 Metropolis-Hastings (MH) algorithm: To explore the posterior distribution of parameters, the most powerful technique is to use Markov chain Monte Carlo (MCMC) computing methods such as the Gibbs sampler (Gelfand and Smith, 1990) and the Metropolis-Hastings (MH) algorithm (Hastings, 1970). While these algorithms enable direct estimation of posterior and predictive quantities of interest, they do not readily lend themselves to estimation aspects of the model probabilities. As a result, many different approaches have been suggested in the literature. The most widely used is the group of direct methods: harmonic mean estimator of Newton and Raftery (1994), importance sampling (Frühwirth-Schnatter, 1995), reciprocal importance estimator (Gelfand and Dey, 1994), bridge sampling ((Meng and Wong, 1996), (Frühwirth-Schnatter, 2002)).

A nice review of some these methods together with background concepts of Bayesian model selection can be found in Kass and Raftery (1995). In 1995 Chib proposed also an indirect method for estimating model likelihoods from Gibbs sampling output, an idea that recently has been extended to output from MH algorithm (Chib and Jeliazkov, 2001). A slightly more direct approach to compute posterior model probabilities using MCMC is to include the model indicator as a parameter in the sampling algorithm itself. Green (1995) introduced a reversible jump MCMC strategy for generating from the joint posterior distribution based on the standard MH approach.

7.1.2 GARCH-type model: The purpose was to give the computationally complete review of these methods and to demonstrate the differences and difficulties of the
model likelihood estimators discussed above by a simulation study and empirical data. Researchers focused on the most important practical models for financial time series -GARCH-type models, introduced for the first time in Bollerslev (1986) and then extensively generalized in many aspects, including conditional variance equation and the density specification. They limited ourselves to the case of two models: AR(1)-GARCH(1,1) with Gaussian errors and AR(1)-GARCH(1,1) with Student density.

The motivation for choosing the GARCH-type models for the illustration was explained by the fact that these models represent a very wide class of heteroskedastic econometric models and, therefore, the Bayesian analysis can be generalized for the whole this class. The Bayesian inference on GARCH-type models has been first implemented using importance sampling [Kleibergen and van Dijk (1993)]. More recent approaches included Griddy-Gibbs sampler by Bauwens and Lubrano (1998) and Metropolis-Hastings algorithm with some specific choice of the proposal distribution (Kim, Shephard and Chib, 1998), (M¨uller and Pole, 1998) and (Nakatsuma, 2000)), the model selection based on the reversible jump MCMC in Vrontos, and on the bridge sampling algorithm (Fr´uhwirth-Schnatter, 2002).

The approach differed from the above that they applied different methods for making Bayesian model choice and compare their performance with the results from the classical analysis. Moreover, they compared the MCMC posterior output with the maximum likelihood estimates of the chosen GARCH models.
The empirical analysis was based on return series of stock indices from different financial markets. They used return series of the Dow Jones Industrial Average (USA), FTSE 100 (Great Britain) and Nikkei 225 (Japan) over a period of 10 years and performed the complete Bayesian inference of GARCH models on these data.

7.1.3 The final works in this connection were given below: A comprehensive review and comparison of five computational methods were presented for Bayesian model selection, based on MCMC simulations from posterior model parameter distributions. Researchers applied these methods to a well-known and important class of models in financial time series analysis, namely GARCH and GARCH-t models for conditional return distributions (assuming normal and t-distributions). They compared their performance vis-à-vis the more common maximum likelihood-based model selection on both simulated and real market data. All five MCMC methods proved feasible in both cases, although differing in their computational demands. Results on simulated data show that for large degrees of freedom (where the t-distribution becomes more similar to a normal one), Bayesian model selection results in better decisions in favour of the true model than maximum likelihood. Results on market data show the feasibility of all model selection methods, mainly because the distributions appear to be decisively non-Gaussian.

7.1.4 Bayesian approach: The interested persons reviewed it to model selection and discussed some computational algorithm. The GARCH-type models chosen for the numerical illustration were presented. Full MCMC methodology includes the detailed
implementation and guidelines of the computational aspects. It was dedicated to the simulation study and the application to market data was included. Some finding were given as follow: Researchers gave a review of popular model selection methods in the Bayesian frame-work, such as harmonic mean, reciprocal sampling, bridge sampling, Chibs’ candidate formula and reversible jump MCMC algorithm.

7.1.5 MCMC simulations: In addition, they compared its accuracy with maximum likelihood estimators over the considered data groups. The mean parameters were estimated in both cases with the same accuracy. With respect to the variance parameters, the calculated estimation errors of the maximum likelihood procedure seem to be in general lower compared to the MCMC results.

They can explain this effect by the non-symmetrical and non-normal shape of the posterior densities for the variance parameters and, therefore, the taken posterior statistics like mean and median of these distributions are not completely adequate. These results for the mean and variance parameters are not correlated with the kurtosis of the ”true” conditional distribution.

As regards the degree of freedom parameter, they got the opposite picture. With the increase of the ”true” degree of freedom value the accuracy of maximum likelihood estimates is getting very low compared to the posterior statistics. It seems that the Bayesian approach by its ”subjectivism” (in the choice of the priors) can manage a situation like this. Again, all results above were not sensitive to the level of the variance persistence.
In the empirical study they performed complete Bayesian analysis of the GARCH models for the stock index returns from the three largest financial markets. As expected they got the overwhelming superiority of the fat-tailed conditional distribution for all data considered.

Section II - The posterior distribution and two dimensional model for blood cancer:

7.2.1 The posterior distribution

It helps you to judge how quickly the MCMC procedure converges in distribution, and how quickly it forgets its starting values.

7.2.2 Conclusion: The posterior distribution appears to be centred at some value mean as (–0.3) which agrees with the mean value for this parameters. Notice that more than half of the sampled values are to the left of 0. This provides mid evidence that the true value of the covariance parameters is negative, but this result is not statistically significant because the proportion to the right of 0 is still quite large. So blood cancer patients are strongly diagnosed through this seventh model.
7.2.3 Two dimensional model: Ranging from dark to light, the three shades of gray represent 50%, 90%, and 95% credible regions, respectively. A credible region is conceptually similar to a bivariable confidence region that is familiar to most data analysis acquainted with classical statistical inference methods.

7.2.4 Credible intervals: Recall that the summary table in the Bayesian SEM window displays their lower and upper endpoints of a Bayesian credible interval for each estimand. By default, Amos presents a 50% interval, which is similar to a conventional 50% confidence interval.

7.2.5 Researchers often report 95% confidence intervals, and so changes in the boundaries to correspond to a Posterior probability content of 95% are expected.
7.2.6 Conclusion: Ranging from dark to light, the three shades of gray represent 50%, 90% and 95% credible region respectively. A credible region is conception similar to a bivariate confidence region that is familiar to most data analysis acquainted with classical statistical inference methods.

All components of class Lymphatics, Block of affarcc, Bolck of lymph s, By pass, Block of lymph c, extravasatee, regeneration of , early uptake in, lym nodes dimin, lym nodes enlar, change in lym, defect in node, changes in node, changes in
strue, special forms, exclusion of node, number of nodes in, and dislocation are strongly enough diagnose as the patient in blood cancer conformably.

**Section III - The posterior distribution and two dimensional model for Breast cancer:**

**7.3.1 The posterior distribution:** It helps you to judge how quickly the MCMC procedure converges in distribution, and how quickly it forgets its starting values.

![Graph showing the posterior distribution](image)

**7.3.2 Conclusion:** The posterior distribution appears to be centred at some value mean (– 0.25) which agrees with the mean value for this parameters. Notice that more than half of the sampled values are to the left of 0. This provides mid evidence that the true value of the covariance parameters is negative, but this result is not statistically significant because the proportion to the right of 0 is still quite large. So breast cancer patients are strongly diagnosed through this seventh model.

164
7.3.3 Two dimensional model for breast cancer
7.3.4 Conclusion: The informations in all components of Menopause, Tumor size, Age, class, Inv-nodes, Node-Caps, Dep-malig, Breast, Breast-quad, and Irradiat, are enough to conformably diagnose as the patient in breast cancer.

Section IV – The posterior distribution and two dimensional model for Primary cancer

7.4.1 The posterior distribution: It helps you to judge how quickly the MCMC procedure converges in distribution, and how quickly it forgets its starting values.
7.4.2 Conclusion: The posterior distribution appears to be centred at some value nearest 0, which agrees with the mean value for this parameters. Notice that more than half of the sampled values are to the left of 0. This provides mid evidence that the true value of the covariance parameters is negative, but this result is not statistically significant because the proportion to the right of 0 is still quite large. So primary tumor cancer patients are strongly diagnosed through this seventh model.

7.4.3 Introduction (two dimensional model): The discussion was first about “Prediction non-stationary processes using Reversible MCMC Arin Chaudhuri, Monsterrat Fuentes, and David Holland. The studies are analyzed first in Atmospheric pollution, RJMCMC, empirical orthogonal functions, and Spatial processes.

Atmospheric pollutants have significant impact on health. The same chemical properties that allow high concentrations of ozone to react with organic material outside the body give it the ability to react with similar organic material that makes up the body, and potentially cause harmful health consequences. When inhaled, ozone can damage the lungs. Relatively low amounts can cause chest pain, coughing, shortness of breath, and, throat irritation. CASTNet (Clean Air status and trends Network).

7.4.5 Atmospheric pollution: Ozone may also worsen chronic respiratory diseases such as asthma and compromise the ability of the body to fight respiratory infections. To study the the impact of various atmospheric pollutants health and terrestrial and aquatic aqua-systems the Clean Air Act Amendments (CAAA) established a monitoring network to to assess improvements in air quality throughout the United
States. To meet the objective Clean Air status and trends Network (CASTNet) was established by the United States Environment Protection Agency (EPA) to monitor rural areas. CASTNet is made up of 51 sites mostly in eastern United States. CASTNet monitors various pollutants including Ozone (O$_3$), sulfur dioxide (SO$_2$), Nitric Acid (HNO$_3$). The CAAA also established ambient air quality standards for carbon monoxide (CO), lead (Pb), nitrogen dioxide (NO$_2$), particulate matter and Ozone. State and Local Air Monitoring Network Stations (SLAMS) and National Air Monitoring Stations (NAMS) were set up to monitor compliance with the air quality standards, these monitors are predominantly in the urban areas. In this paper we study the distribution Ozone from the SLAMS / NAMS / CASTNet networks. The distribution of Ozone is known to exhibit non-stationary behavior, and so the spatial distribution of Ozone depends on where it is being measure, taking this into consideration we fit a hierarchical Bayesian model arising out of the convolution of stationary processes centered at various locations. This work do not assume the number of local stationary process required to fit the data adequately to be known in advance and hence our model consists of a variable number of parameters and researchers used the methods of RJMCMC to determine the number of the processes and to estimate their parameters.

It contains a literature review of the work done in non-stationary modeling so far. In recent years, probably the most extensively studied method for non-stationary spatial processes is the deformation approach. In a series of works represented by Timothy C. Haas (1990), T. Haas has proposed an approach to non-stationary spatial
kriging based on moving windows. Researchers give a model for accounting for heterogeneity in the spatial covariance function of a spatial process, using a moving average specification of a Gaussian process. Another approach has been developed that extends the “empirical orthogonal functions” (EOF) approach that is popular among atmospheric scientists. It describes below these approaches to modeling non-stationarity in the spatial context.

In the above approach, the function f might be a mapping from $\mathbb{R}^2$ to $\mathbb{R}^d$ where might be greater than two, but they assume $d=2$ in their applications. People have also approached the problem in a bayesian framework in which they estimate the deformed coordinates and the parameters of the correlation function and the variance parameters. In the Bayesian case they parametrize the dispersion between two points and so they consider the following form $\rho_\theta |f(x_1) - f(x_2)|$ where $\rho_\theta$ is a known parametric family.

7.4.6 **The final works were given below:** Spatial processes for air pollutants defined over large geographic areas rarely exhibit stationary behavior. We propose a non-stationary spatial covariance model that is a mixture of stationary processes. The number of stationary processes and their parameters are estimated using a Reversible Jump MCMC approach in a hierarchical Bayesian framework. We also introduce methods for an efficient implementation and fast computation. We apply this method to the modeling, prediction of ambient ozone in the Eastern US.
7.4.7 Conclusion: The informations in Class, Age, Sex, Histologic-type, Degree-of-diffe, Bone, bone-marrow, lunc, pleura, peritoneum, liver, brain, skin, neck, supraclavicular, axillar, mediastinum and abdominal of primary tumor are enough to diagnose as the patient in primary tumor conformably.