Approximate Bayesian Inference for Spatial Econometrics with R-INLA

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Keywords: Bayesian Inference, INLA, Spatial Econometrics

LeSage and Pace [2] describe several models for Spatial Econometrics and provide some software to fit them in the Spatial Econometrics Toolbox for Matlab (http://www.spatial-econometrics.com/). Many of these models rely on spatially autoregressive effects, such as

$$y = \rho W y + X \beta + \varepsilon \tag{1}$$

where y is a vector of observed data, ρ a spatial autocorrelation parameter, X a matrix of covariates with associated coefficients β and ε is a Gaussian random error. Equation (1) can be rewritten as

$$y = (I_n - \rho W)^{-1} (X\beta + \varepsilon)$$
(2)

which shows how the response y depends on some latent spatial effects.

In this work we will introduce the use of the Integrated Nested Laplace Approximation [3, INLA], as implemented in the **R-INLA** package, to fit a wider range of spatial econometrics models. INLA provides a suitable methodology to estimating the posterior marginal of the model parameters when the latent effects are Gaussian Markov Random Fields. Some latent effects are implemented in the **R-INLA** package so that models can be defined and fitted similarly with the inla() function, similarly as with glm() or gam().

We will consider two different approaches. The first one is described in Bivand et al. [1] and it is very helpful when the latent model that we need is not implemented in **R-INLA**. Instead of fitting the required model, this method is based on fitting that model after conditioning on different values some of the parameters in the model and then combining them using Bayesian model averaging (with package **INLABMA**) to obtain the desired model. These conditioned models are often simpler than the original model and can be easily fitted with **R-INLA**.

The second approach is based on a newly implemented latent model that provides random effects required for several spatial econometrics models as in equation (2). This approach to model fitting is preferable because it is completely implemented in **R-INLA** and does not require any other external code.

Finally, we will describe how to use these models on two real datasets on the housing value in Boston and the probability of re-opening a business in New Orleans in the aftermath of hurricane Katrina.

References

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