Bayesian Structured Additive Distributional Regression

Nadja Klein
Chair of Statistics, Georg-August-University Göttingen
nklein@gwdg.de

Innsbruck, December 4, 2013

Classical regression models within the exponential family framework such as generalised linear models or generalised additive models focus exclusively on relating the mean of a response variable to covariates but neglect the potential dependence of higher order moments or other features of the response distribution on covariates. As a consequence, the advantage of obtaining covariate effects that are straightforward to estimate and easy to interpret is at least partly offset by the likely misspecification of the model. A completely distribution-free alternative to mean regression is provided by quantile or expectile regression which have the distinct advantage that basically no assumptions on the specific type of the response distribution are required. However, if prior knowledge on specific aspects of the response distribution is available, quantile and expectile regression may be less efficient and are also less appropriate for discrete or mixed discrete continuous distributions.

Therefore, it is of considerable interest to derive models that are in between the simplistic framework of exponential family mean regression and distribution-free approaches. Such an approach is given by the class of generalised additive models for location, scale and shape (GAMLSS, Rigby and Stasinopoulos, 2005). In the spirit of GAMLSS, we develop a generic Bayesian treatment of distributional regression relying on efficient Markov chain Monte Carlo simulation algorithms, which allow to decompose all model predictors additively in a variety of different functional effect types such as nonlinear effects, spatial effects, random coefficients, interaction surfaces or other (possibly non-standard) basis function representations.

The talk is supposed to give basic ideas about the framework of GAMLSS and inference in Bayesian structured additive distributional regression. Its relevance is demonstrated in several real data applications.

References

Klein, N., Kneib, T., Lang, S., 2013a. Bayesian Generalized Additive Models for Location, Scale and Shape for Zero-Inflated and Overdispersed Count Data. Technical Report, http://econpapers.repec.org/paper/innwpaper/2013-12.htm.

Klein, N., Kneib, T., Lang, S., 2013b. Bayesian Structured Additive Distributional Regression. Technical Report, http://econpapers.repec.org/paper/innwpaper/2013-23.htm.

Klein, N., Denuit, M., Kneib, T., Lang, S., 2013c. Nonlife Ratemaking and Risk Management with Bayesian Additive Models for Location, Scale and Shape. Technical Report, http://econpapers.repec.org/paper/innwpaper/2013-24.htm.

Rigby, R.A., Stasinopoulos, D.M., 2005. Generalized additive models for location, scale and shape (with discussion). Applied Statistics 54, 507–554.