

Discussion of the John Geweke and Sylvia Frühwirth-Schnatter talks about Label Switching in mixtures

Gilles Celeux

Inria Saclay-Île-de-France

March 3 2010

John : "The multimodal posterior introduces no complications for MCMC posterior simulators."

- ▶ I agree that virtual **permutation-augmented** simulators solve the problem for well-separated component mixtures since the MCMC algorithms stay in a single modal region.
- ▶ And multimodality does not provoke MCMC slow convergence (but, no multimodal MCMC sequences indicate slow convergence).
- ▶ Otherwise **reordering** the parameters is an important and not easy task directly related to the labeling problem.
- ▶ For instance, labeling is an important issue for RJMCMC samplers.

Relabeling MCMC draws

Various methods have been proposed to reorder MCMC draws.

- ▶ A reference paper is Stephens (2000) which proposes a method among the most efficient one in practice. It is relying upon specifying a loss function and is minimising its posterior expected loss with a k -means like algorithm on the **conditional probabilities** than a point arises from one of the mixture components.
- ▶ An interesting extension is the probabilistic approach of Sperrin *et al.* (2009) which allows for incorporation of the uncertainty in the relabeling process.
- ▶ But all these methods require to identify $K!$ clusters.

The Point process representation of the MCMC draws

- ▶ It is a great interest of the *Sylvia* k -means clustering method in the **point process representation** of the MCMC draws to identify K clusters instead of $K!$ clusters.
- ▶ Since the vector parameters to be clustered could be of high dimension, *Sylvia* suggests to consider a **subset** of the component-specific parameters to obtain the clustering sequences.

I agree to think that this reduction of dimension is highly desirable.

- ▶ But, choosing such a **subset** could be rather influential and delicate. . .
- ▶ Some "data analyst" talents could be required to make a sensible choice, while the Stephens labeling method avoids to work in the mixture parameter space. . .

The Role of the Prior on the Weight Distribution

In the Part II of the [Sylvia](#)'s talk, I have been impressed by her demonstration of the great influence of the Prior on the mixing weights to select the number of mixture components.

- ▶ The example that she considered ($K^{\text{true}} = 2, \mu_1 = -4, \mu_2 = 3, \sigma_1^2 = \sigma_2^2 = .5, \eta_1 = .2$) with $n = 1000$ is a mixture with quite well separated components.
- ▶ Any penalized information criteria (BIC, ICL and even AIC) will sharply choose $K = 2$ for this example.
- ▶ My feeling, after her bright demonstration, is that choosing "non informative" Priors for mixture models remains quite challenging (see also Aitkin 2002).

Is Bayesian model-based clustering possible?

Model-based cluster analysis is one of the most important domain of application of mixture models. In this setting, n , d are large and K could be large as well.

To day, I see no reason to favor the Bayesian view point for **model-based cluster analysis**...

- ▶ It is clear that the Bayesian point of view can be fruitful for estimating mixtures for ill-posed problems (same sample sizes, overlapping components) (see Dias and Wedel 2004) but only for **low** dimensions and **small** number of mixture components.
- ▶ But, in most situations, the advantage of Bayesian inference over **maximum likelihood** inference is unclear for estimating mixture models.

References

Aitken, M. (2001), Likelihood and Bayesian analysis of mixtures, *Statistical Modelling*, 1, 287-304.

Dias, J. G. and Wedel, M. (2004), An empirical comparison of EM, SEM and MCMC performance for problematic Gaussian mixture, *Statistics and Computing*, 14, 323, 332.

Sperrin, M., Jaki, T. and Wit, E. (2010) Probabilistic relabeling strategies for the label switching problem in Bayesian mixture models, *Statistics and Computing* (to appear) [available on line](#).

Stephens, M. (2000). Dealing with label switching in mixture models, *Journal of the Royal Statistical Society, B*, 62, 795–809.