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# Label switching in mixtures



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## The label switching problem

### Mixture of $g$ distributions

$$p(\cdot|\theta) = \sum_{k=1}^g \alpha_k p(\cdot|\beta_k)$$

- $\alpha_k$ : mixtures weights ( $\alpha_k > 0$  and  $\sum_k \alpha_k = 1$ )
- $\beta_k$ : parameters of each component distribution
- $\theta_k = (\alpha_k, \beta_k)$
- $\theta = (\theta_1, \dots, \theta_g) \in \Theta$

### Generative interpretation

$x = (x_1, \dots, x_n)$  an  $n$  i.i.d. sample from  $p(\cdot|\theta)$   
 $z = (z_1, \dots, z_n) \in \mathcal{Z}$  is the *latent partition* which as been used to generate  $x$

- $z_i \sim \mathcal{M}(1; \alpha_1, \dots, \alpha_g)$
- $x_i \sim p(\cdot|\beta_{z_i})$

### Bayesian framework

- $p(\theta)$  a prior distribution on  $\theta$
- Bayesian inference is based on the posterior distribution  $p(\theta|x) \propto p(x|\theta)p(\theta)$

### The problem

If  $p(x|\theta)$  and  $p(\theta)$  are invariant up to a mixture component renumbering then so does  $p(\theta|x)$

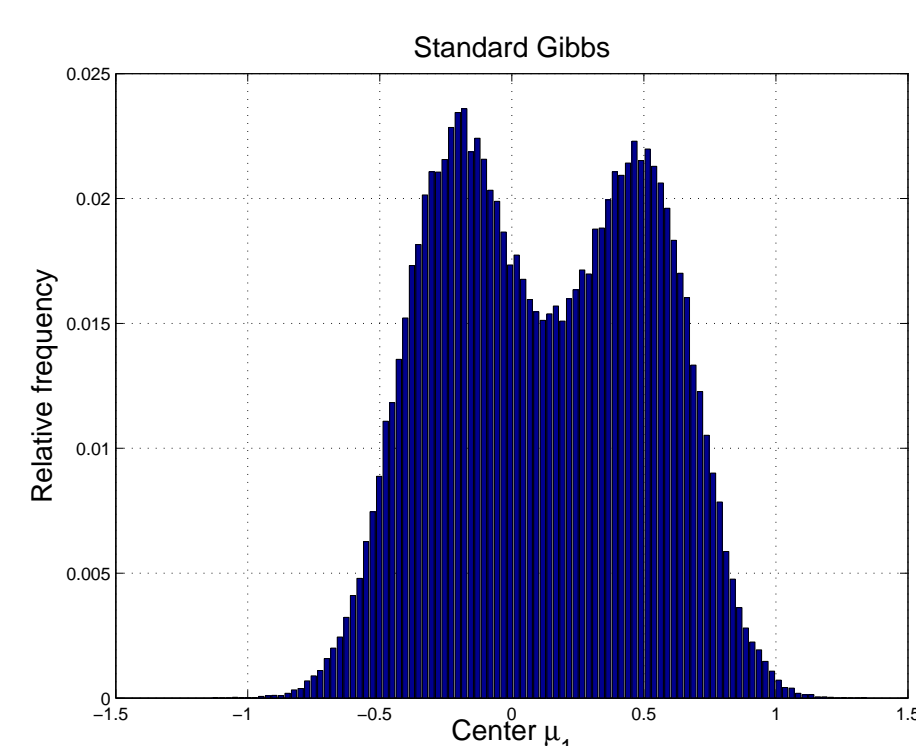
- $\mathcal{P}_g$  is the set of  $\{1, \dots, g\}$  permutations
- $\sigma(\theta) = (\theta_{\sigma(1)}, \dots, \theta_{\sigma(g)})$  is the parameter  $\theta$  permuted in index with  $\sigma \in \mathcal{P}_g$

$$p(\theta|x) = p(\sigma(\theta)|x)$$

This exact symmetry is called *label switching*. It then makes meaningless direct computation of many usual punctual estimators as the posterior mean. The aim of many approaches is to remove this symmetry.

## Illustration of the problem

- Two univariate components ( $g = 2$ )
- $p(\cdot|\beta_k) = \mathcal{N}(\beta_k, 1)$
- $\alpha_1 = \alpha_2 = 0.5$
- Proportions and variances known and fixed
- Mean  $\theta_1 = \beta_1$  et  $\theta_2 = \beta_2$  unknown
- Prior distributions on  $\theta_k \sim \mathcal{N}(0, 1)$  with  $\theta_1 \perp \theta_2$
- Posterior distributions
  - ▶  $\theta_k|z, x \sim \mathcal{N}(n_k \bar{x}_k / (n_k + 1), 1/(n_k + 1))$
  - ▶  $z_i|\theta, x \sim \mathcal{M}_2(1, t_{i1}(\theta), t_{i2}(\theta))$
  - ▶  $n_k = \sum_{i=1}^n \mathbb{I}_{z_i=k}$
  - ▶  $\bar{x}_k = \sum_{i=1}^n \mathbb{I}_{z_i=k} x_i / n_k$
  - ▶  $t_{ik}(\theta) = p(z_i = k|x, \theta)$
- $\theta_1 = 0$  and  $\theta_2 = 0.25$



Two modes can be seen on the posterior distribution of  $\theta_1$  when only one would be expected in absence of label switching. It is then impossible to make relevant analysis of the posterior distributions component-wise.

## Standard solutions

### Modified prior distribution

- Artificial identifiability constraints on the parameters (Diebolt et Robert, 1994)
- Ordering constraints :  $\theta_1 < \theta_2$
- Modification of the prior distribution which becomes proportional to  $p(\theta)\mathbb{I}_{\theta_1 < \theta_2}$
- Not enough to solve the label switching problem (Celeux et al., 2000 ; Jasra *et al.*, 2005)

### $k$ – means algorithm on the parameters space

- Relabeling algorithm of the generated parameters (Stephens, 1997 ; Celeux, 1998)
- Find the permutation for the fixed parameter which minimizes a loss function
- $k$  – means type algorithm on the parameters space
- Underestimation of the dispersion of the posterior distribution

### Invariant loss function

- Loss function invariant up to the parameters permutation (Celeux et al., 2000)
- Choice of a loss function adapted to the inferential problem
- Optimization of this last

### Probabilistic relabeling

- Probabilistic approach (Jasra et al., 2005) to take into account the uncertainty of the attribution of the permutation to the parameters
- Model on the deswitched posterior distribution learned from an unswitched sequence
- Probability for each permutation of the parameter get by the Gibbs sampler
- Computation of quantities of interest such as the posterior mean

### Bibliographic overview

- Methods allowing to partially solve the problem
- Problem when posterior distributions are poorly separated, tuning parameters to set
- The latent partition is not taken into account

The *latent partition* is now used to solve the label-switching problem

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## Idea: using the numbering information

$\tilde{\mathcal{Z}} = \{\mathcal{Z}_1, \dots, \mathcal{Z}_{g!}\}$  a partition of the set of partitions  $\mathcal{Z}$ . It sets a particular numbering for each partition  $z$  of the dataset  $x$

$$\forall h, h' \in \{1, \dots, g!\}, \exists! \sigma \in \mathcal{P}_g \text{ tq } z \in \mathcal{Z}_h \Leftrightarrow \sigma(z) \in \mathcal{Z}_{h'}$$

with  $\sigma(z) = (\sigma(z_1), \dots, \sigma(z_n))$  indicating that  $z$  is permuted in indexes for  $\sigma \in \mathcal{P}_g$ .  
 Decomposition of the usual posterior distribution as a mixture of  $g!$  posterior distributions conditioned by any particular numbering  $\tilde{\mathcal{Z}}$  of the partitions.

- $\tilde{\mathcal{Z}}$  is unknown but it corresponds to a latent numbering information
- $p(\theta|x, \mathcal{Z}_h)$  not strictly invariant up to a renumbering of  $z$
- The asymmetry depends on the choice of  $\tilde{\mathcal{Z}}$
- Choose the cutting  $\tilde{\mathcal{Z}}$  which separates the best the distributions  $p(\theta|x, \mathcal{Z}_h)$
- Keep as new definition of the posterior distribution any of these  $g!$  distributions

$$p(\theta|x) = \sum_{h=1}^{g!} p(\theta|x, \mathcal{Z}_h) p(\mathcal{Z}_h|x) = \frac{1}{g!} \sum_{h=1}^{g!} p(\theta|x, \mathcal{Z}_h).$$

## Choosing a $g!$ fraction $\tilde{\mathcal{Z}}$ of $\mathcal{Z}$

### Choice 1: $\tilde{\mathcal{Z}}^{KL}$

$\tilde{\mathcal{Z}}^{KL}$  maximizes the Kullback-Leibler divergence between the mixture components on  $\mathcal{Z}_h$  which is written

$$\tilde{\mathcal{Z}}^{KL} = \arg \max_{\tilde{\mathcal{Z}}} \min_{h=2, \dots, g!} \int_{\Theta} p(\theta|x, \mathcal{Z}_1) \ln \left[ \frac{p(\theta|x, \mathcal{Z}_1)}{p(\theta|x, \mathcal{Z}_h)} \right] d\theta.$$

Intractable even for very small sample sizes.

### Choice 2: $\tilde{\mathcal{Z}}^{MAP}$

$$\tilde{\mathcal{Z}}^{MAP} = \arg \max_{\tilde{\mathcal{Z}}} \min_{h=2, \dots, g!} \frac{p(\theta^{MAP}|x, \mathcal{Z}_1)}{p(\theta^{MAP}|x, \mathcal{Z}_h)}.$$

It is equivalent to find the most probable numbering unit by unit computed in  $\theta^{MAP}$  :

$$\mathcal{Z}_1^{MAP} = \left\{ z \in \mathcal{Z} / Id = \arg \max_{\sigma \in \mathcal{P}_g} p(\sigma(z)|x, \theta^{MAP}) \right\},$$

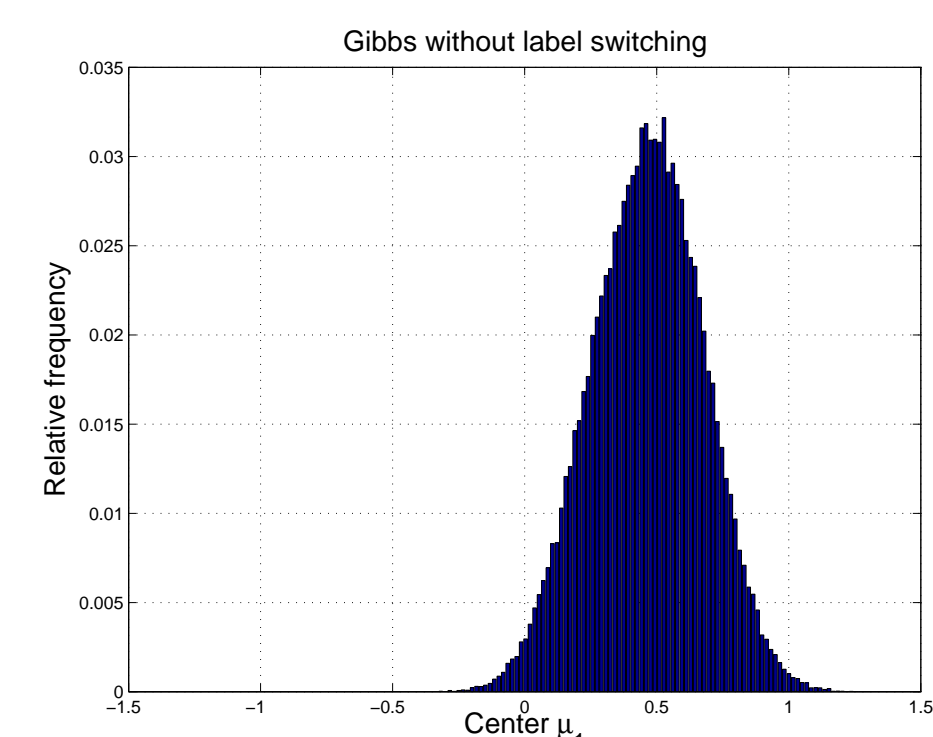
$Id$  is the identity permutation.  $\theta^{MAP}$  is the reference parameter for the numbering of the latent partition.

## Proposed Gibbs algorithm

The classical Gibbs algorithm is slightly modified

- $z \sim p(\cdot|x, \theta)$ ,
- $z$  permuted in order to  $\sigma(z) \in \mathcal{Z}_1^{KL}$  or  $\sigma(z) \in \mathcal{Z}_1^{MAP}$
- $\theta \sim p(\cdot|x, \sigma(z))$

Additional algorithmic complexity negligible for  $\mathcal{Z}_1^{MAP}$ .



## Numerical experiments

### Experiments in the Gaussian setting (running example continued)

	Strategy	$n = 3$	$n = 10$	$n = 100$
• 100 samples $x$ of size $n \in \{3, 10, 100\}$	Gibbs/ $k$ -means	0.18648 (0.10316)	0.09613 (0.09677)	0.02594 (0.04200)
• Burning sequence of 100 iterations	KL	0.03358 (0.04357)	NA	NA
• 2,000 iterations of Gibbs	MAP	0.03372 (0.04679)	0.06135 (0.08815)	0.02364 (0.04157)

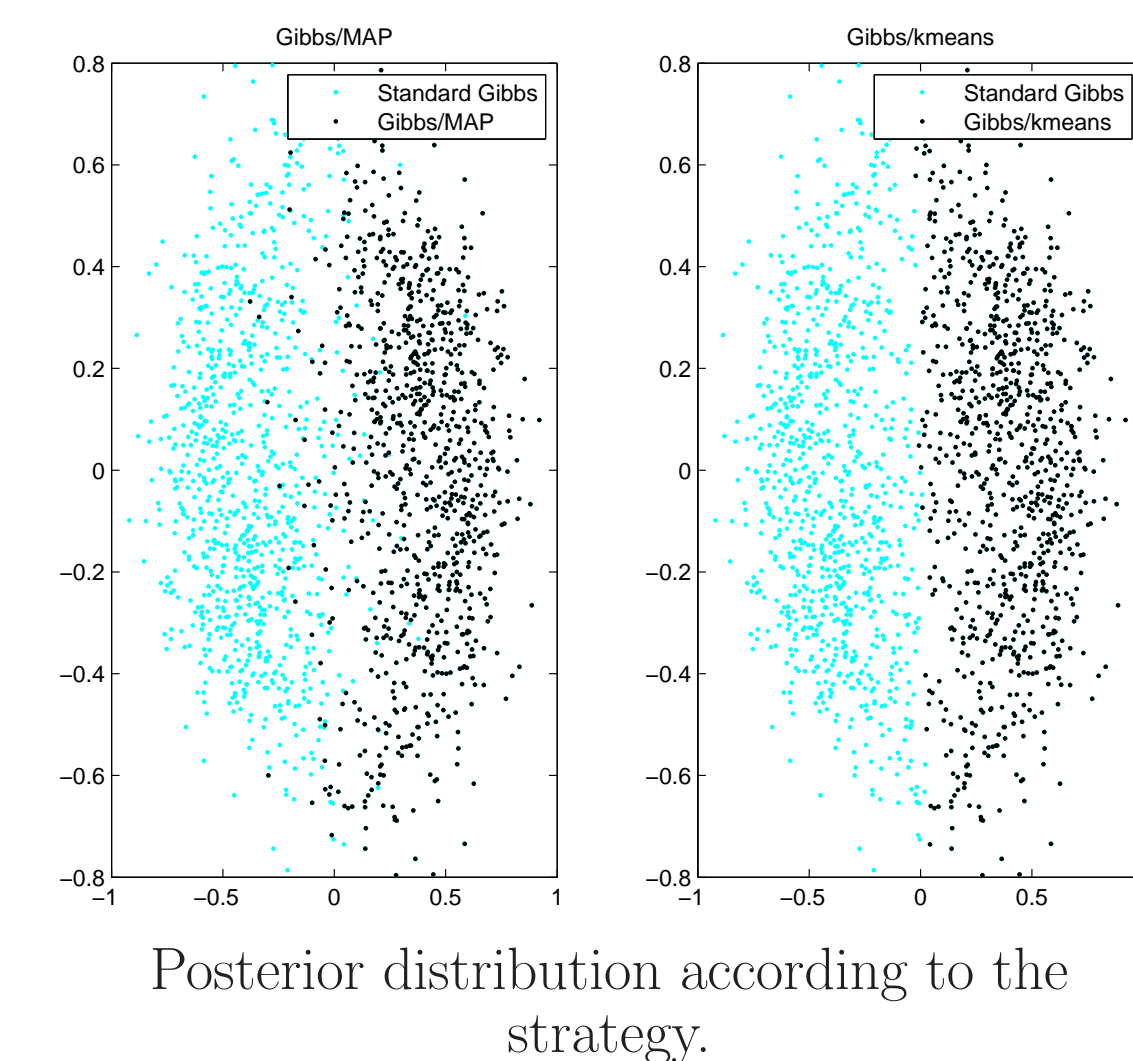
Mean (and standard deviation) of the posterior mean square error.

### Experiments in the multinomial product mixture setting

- Qualitative simulated data with  $g = 2$  poorly separated classes in equal proportions
- 6 variables: 4 with 3 modalities and 2 with 4 modalities
- Estimated model: mixture of  $g = 2$  products of multinomial distributions, all parameters free
- 100 samples of sizes  $n = 50$
- Burning sequence of 1,000 iterations
- 10,000 iterations of Gibbs

Strategy	$n = 50$
Gibbs/ $k$ -means	0.10949 (0.04588)
MAP	0.10627 (0.04549)

Mean (and standard deviation) of the Kullback divergence to the true distribution.



## Conclusion and perspectives

### Conclusion

- Separation of the posterior modes without break
- Assumption free on the unswitched distribution
- Computational cost similar to standard solutions

### Perspectives

- Monitor the convergence of the Gibbs algorithm
- Many application areas: hidden Markov models, Potts model, ...