

 $\Box$  p.  $r$  and of information  $\mathcal{A}$  in  $\Box$   $\mathcal{A}$  bool of  $\Box$   $\Box$  $\clubsuit$ Des $_p$ AA, P $_p^{\prime}$  Des $_r$ , P $_p^{\prime}$ , 100871, P $_p^{\prime}$ p, jwma@math.pku.edu.cn

**Abstract.** Gaussian mixture has been widely used for data modeling .  $p_A$  ,  $p_B$  is generally employed for its particles in the EM algorithm is generally employed for its particle in  $\frac{1}{2}$  or  $\frac{1}{2}$  in  $\frac{1}{2}$  in  $\frac{1}{2}$  in  $\frac{1}{2}$  in  $\frac{1}{2}$  in  $\frac{1}{2}$  in  $\frac{1}{2}$  in rameter learning. However, the EM algorithm may be trapped into a second into a s o and of  $\mathfrak{b}$  boo<sub>d</sub>  $\mathfrak{p}_A$  **p** as o ro $\mathfrak{p}_E^*$  result  $\mathbb{P}$  p brof oponess not poropring is not appropriately set. petitive  $(\mathcal{F}_{\mathbb{C}}^{\bullet})$  and  $\mathcal{F}_{\mathbb{C}}^{\bullet}$  for Gaussian mixtures, a new  $r_{\mathbb{S}},$  and  $r_{\mathbb{S}},$  and  $r_{\mathbb{S}}$  $\mathbf{s}_1$ plit $\mathbf{p}_2$  is a greater learning algorithm with competitive mechanism  $\mathbf{p}_1$  is a greater mechanism of  $\mathbf{p}_2$  is a greater mechanism of  $\mathbf{p}_1$  is a greater mechanism of  $\mathbf{p}_2$  is a greater mechanism on  $\mathrm{s}$  and  $\mathrm{pos}$  algorithm, has been constructed to  $\mathrm{pos}$ oro  $\mathbb{P}_S$  are backs.  $\mathbb{P}_S$  ,  $\mathbb{P}_S$  ,  $\mathbb{P}_T$  ,  $\mathbb{P}_S$  ,  $\mathbb{P}_T$  ,  $\mathbb{P}_T$  ,  $\mathbb{P}_T$  ,  $\mathbb{P}_T$  ,  $\mathbb{P}_T$ rithm through it is a separated the Bayesian Yang  $\mathbb{Z}^2$  of  $\mathbb{Z}^2$  (by  $\mathbb{Z}^2$  or  $\$  $\mathbb{P}_S$  a of  $\mathbb{P}_P$  proges  $\mathbb{P}_S$  used  $\mathbb{P}_S$  the metrope  $\mathbb{P}_S$  is a  $\mathbb{P}_S$  or  $\mathbb{P}_S$  is defined by the metrope  $\mathbb{P}_S$  $\mathrm{s}$  on props that orgropo $\mathrm{s}$  algorithm algorithm outperforms  $\frac{1}{2}$  or  $\frac{7}{2}$  p one one both  $\frac{1}{2}$   $\frac$ 

**Keywords:**  $\blacksquare$ ompetitive  $(\blacksquare - ) \cup \spadesuit$ ori $\blacksquare$ ,  $\blacksquare$   $\blacksquare$ ,  $\blacksquare$   $\blacksquare$ ,  $B_S \cdot B \cdot P_{\mathbf{Z}}^2 \cdot P_{\mathbf{Z}}^2$  (b) has one learning,  $\mathcal{O}_A$  setes  $\mathcal{O}_B$ 

As a powerful statistical tool, Gaussian mixture has been widely used in the  $b$  -species  $\mathbf{b}$  -species in the theory used in the  $\mathbf{b}$ fields of signal processing and pattern recognition. In fact, there are  $\bar{I}_s$  is the already existence already existence statistical statistical methods for the Gaussian mixture modeling, such as the k-form  $k$ means algorithm [2]) and the Expectation-Maximization (EM) algorithm [3].  $H_{\rm eff}$  algorithm cannot determine the correct number of  $\sigma$   $\sim$ in the mixture for a sample data set because the likelihood to because the likelihood to be maximized is  $\mathsf{b}$ actually a increasing function of the number of  $b$  , and the number of Gaussians. Moreover, a  $b$ initialization usually makes it trapped at a local maximum, and sometimes the EM algorithm converges to the boundary of the boundary of the boundary of the parameter space. Conventionally, the methods of model selection for Gaussian mixture, i.e., determining a best number  $k^*$  $k^*$  of  $k^*$  of Gaussians for a sample data set, are based on a sample data set, are based  $\mathbf{b} = \mathbf{b} = \mathbf{k}^*$  (AIC)  $\mathbf{c} = \mathbf{b}$  $\begin{split} &\frac{1}{2} \sum_{i=1}^{N} \left\| \frac{1}{\mathcal{B}_{i}} \right\|_{\mathcal{B}_{i}} = \frac{1}{2} \sum_{i=1}^{N} \left\| \$ wrong result.  $\bullet$  orr  $\phi$  or  $\phi$  and  $\phi$  a

D.-S. Huang et al. (Eds.): ICIC 2008, LNCS 5226, pp. 552–560, 2008. c Springer-Verlag Berlin Heidelberg 2008

**1 Introduction**

**The Competitive EM Algorithm for Gaussian**



**2 The EM Algorithm for Gaussian Mixtures**

$$
p \ x | \Theta_k \qquad \sum_{i=1}^k \alpha_i p \ x | \theta_i \qquad \sum_{i=1}^k \alpha_i p \ x | \mu_i, \Sigma_i \ ,
$$

where  $k$  is number of components in the mixture,  $\alpha_i \geq$  0) are the mixing proportions of components satisfying  $\sum_{i=1}^k \alpha_i$  and each component density p  $x|\theta_i$  $d$ , and gaussian probability density function  $d$ 

$$
p \ x|\theta_i
$$
  $p \ x|\mu_i, \Sigma_i$   $\frac{\pi}{2} |\Sigma_i|^{\frac{1}{2}} e^{-\frac{1}{2}(x-\mu)} \Sigma^{-1}(x-\mu),$ 

where μ<sup>i</sup> is the mean vector and Σ<sup>i</sup> is the covariance matrix which is assumed positive definite. For clarity, we let Θ<sup>k</sup> be the collection of all the parameters in the mixture, i.e., Θ<sup>k</sup> = (θi, ··· , θk, α1, ··· , αk).

554  $P_{\mathbf{g}}, \ldots, P_{\mathbf{d}}$ .

$$
N \times S = \mathcal{X} \{x_i\}_{i=1}^{N}
$$
\n
$$
p \times |\Theta_k| = \prod_{t=1}^{N} p x_i |\Theta_k| \sum_{t=1}^{N} \sum_{i=1}^{k} \alpha_i p x_i |\theta_i|,
$$
\n
$$
\Theta_k = \sum_{t=1}^{N} P i |x_t - \mu_i^+ \sum_{t=1}^{N} x_t P i |x_t| / \sum_{t=1}^{N} P i |x_t|
$$
\n
$$
\sum_{i}^{+} \sum_{t=1}^{N} P i |x_t - \mu_i^+ x_t - \mu_i^+ x_t | \sum_{t=1}^{N} P i |x_t|,
$$
\n
$$
P i |x_t - \alpha_i p x_i |\theta_i / \sum_{i=1}^{k} \alpha_i p x_i |\theta_i|.
$$
\n
$$
\sum_{i}^{N} \sum_{i}^{N} P i |x_t - \mu_i^+ x_i | \sum_{i}^{N} P i |x_t|,
$$
\n
$$
\sum_{i}^{N} \sum_{i}
$$

## $\mathbf{b}$   $\bullet$  C<sub>o</sub>mpetitive EM Algorithm for Gaussian Mixtures 555

where  $G$   $\cdot$  is a kernel function and  $q$   $x|y$  in and  $q$   $x|\theta_i$  is a Gaussian density is a Gaussian density function. In this architecture, q  $y$  is a free probability function,  $q$   $x|y$  is a Gaussian density, and p  $y|x|$  is constructed from q  $y$  and  $q$   $x|y$  under the theorem  $q$ Bayesian law.

556  $\mathcal{P}_{\mathbf{g}}^{\mathbf{z}}, \ldots, \mathcal{P}_{\mathbf{d}}$ 



558  $P_{\mathbf{g}}$ ,  $P_{\mathbf{g}}$ ,  $P_{\mathbf{d}}$ .





- <span id="page-8-0"></span>10.  $\ldots$ ,  $\mathbb{F}_2^{\mathbb{Z}}$ ,  $\ldots$  rop  $\mathbb{F}_p^{\mathbb{Z}}$  on  $P$   $\ldots$   $\ldots$  Adaptive  $\mathbb{F}_q$  $\mathbf{p}$  **p**  $\mathbf{p}$ , or  $\mathbf{p}_A$  is a  $\mathbf{p}_B^T$  mechanism. Neural  $\mathbf{p}_B$  is the  $\mathbf{p}_B$  subset of  $\$  $r_S$  24(1), 19–40 (2006)
- 11.  $M_1, M_2, M_3, \ldots, M_n$ . App  $\mathbb{F}_p^{\mathbb{Z}}$  and  $\mathbb{F}_p^{\mathbb{Z}}$  Algorithm for  $\mathbb{F}_q$  is  $p$  in  $M$  $\mathcal{P}$  A o  $\mathcal{A}$  og  $\mathcal{A}$  ov. Pp of  $\mathcal{P}$  ov 40, 2029–2037 (2007)
- 12. Ma,  $M_{\rm B}$   $_{\rm A}$  pop  $_{\rm A}$  rop pp  $_{\rm A}$  A  $_{\rm Z}$  or  $_{\rm SS}$  p  $\mathbf{r} = \mathbf{p} \mathbf{A}$  o  $\mathbf{a}$  o  $\mathbf{a}$   $\mathbf{a}$  or  $\mathbf{r}$  or  $\mathbf{p}$  or  $\mathbf{p}$  or  $\mathbf{r}$  s 29(6), 701– 711 (2008)
- 13. P.  $\nu_{\mathbf{z}}$ , P.  $\nu_{\mathbf{z}}$ , T.,  $\ldots$  T. Op Algorithm for  $P$  for  $P$  algorithm for  $\mathbf{z}_1$ els. Pathern  $\frac{1}{2}$  or 37, 131–144 (2004)
- 14. P.  $\mathbb{Z}_p^{\mathbb{Z}}$ ,  $\mathbb{Z}^{\mathbb{Z}}$  p.,  $\mathbb{Z}_p^{\mathbb{Z}}$ ,  $\mathbb{Z}_p^{\mathbb{Z}}$ ,  $\mathbb{Z}_p$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\mathbb{Z}_p^{\mathbb{Z}}$  and  $\clubsuit$  -  $p_A$ -  $r_E'$  per op. Pattern  $\phi$  of  $\phi$  or 36, 1973–1983 (2003)