ANALYSIS OF THE MAXIMAL A POSTERIORI PARTITION IN THE GAUSSIAN DIRICHLET PROCESS MIXTURE MODEL Łukasz Rajkowski l.rajkowski@mimuw.edu.pl University of Warsaw

This



#### tion can be used 3 5 the • • • rocco $\mathbb{P}(\text{new table}) \propto \alpha$ $\mathbb{P}(\text{join table}) \propto \# \text{ sitting there}$ e.g. $\mathbb{P}\{\{1, 2, 4, 6\}, \{3\}, \{5, 7\}\} = \frac{\alpha}{\alpha} \cdot \frac{1}{1+\alpha} \cdot \frac{\alpha}{2+\alpha} \cdot \frac{2}{3+\alpha} \cdot \frac{\alpha}{4+\alpha} \cdot \frac{3}{5+\alpha} \cdot \frac{1}{6+\alpha}$





and  $A \in \mathcal{A}$  let  $J_n^A = \{i \leq n \colon X_i \in A\}$  and

$$\mathcal{J}_n^{\mathcal{A}} = \big\{ J_n^{\mathcal{A}} \neq \emptyset \colon \mathcal{A} \in \mathcal{A} \big\}.$$

We say that this partition of [n] is *induced* 

## The Gaussian DPMM and the MAP

The Gaussian DPMM for n observations may be modelled as follows

 $\mathcal{J} \sim \operatorname{CRP}(\alpha)_n$  (the Chinese Restaurant P.)  $\boldsymbol{\theta} = (\theta_J)_{J \in \mathcal{J}} \mid \mathcal{J} \stackrel{\text{iid}}{\sim} \mathcal{N}(\vec{\mu}, T)$  $\boldsymbol{x}_J = (x_j)_{j \in J} \mid \mathcal{J}, \boldsymbol{\theta} \stackrel{\text{iid}}{\sim} \mathcal{N}(\theta_J, \Sigma) \text{ for } J \in \mathcal{J}$ 

The partition that maximises the posterior probability is the MAP partition. It is denoted by  $\mathcal{J}(x_1,\ldots,x_n)$ .

# **RESULT 1.** Convexity of the MAP

For every  $n \in \mathbb{N}$  if  $J_1, J_2 \in \hat{\mathcal{J}}(x_1, \ldots, x_n), J_1 \neq J_2$  and  $A_k$  is the convex hull of the set  $\{x_i: i \in J_k\}$  for k = 1, 2 then  $A_1 \cap A_2$  is an empty set or a singleton  $\{x_i\}$  for some  $i \leq n$ .



Assume that P has bounded support and is continuous with respect to Lebesgue measure. Then the distance between  $\mathcal{A}_n$  and the set of partitions that maximise the function  $\Delta$ converges to 0.



(a) This is the desired partition (b) This is a convex partition (c) This partition is not convex and which is also convex. which is not ideal. it is clearly a bad one.

## **RESULT 2. Which clusters are big?**

If  $\sup_{n} \frac{1}{n} \sum_{i=1}^{n} ||x_n||^2 < \infty$  then  $\liminf_{n \to \infty} \min\{|J| \colon J \in \hat{\mathcal{J}}(x_1, \dots, x_n), \exists_{j \in J} ||x_j|| < r\}/n > 0$ for every r > 0.



**Corollary.** If  $\left(\frac{1}{n}\sum_{i=1}^{n} ||x_i||^2\right)_{n=1}^{\infty}$  is bounded then for every r > 0 the number of clusters that intersect  $B(\mathbf{0}, r)$  is bounded.

### **Result** 4. The force of $\Sigma$

Assume that P has bounded support and is continuous with respect to Lebesgue measure. Then for every  $K \in \mathbb{N}$  there exists an  $\varepsilon > 0$  such that if  $\|\Sigma\| < \varepsilon$  then  $|\mathcal{J}_n| > K$  for sufficiently large n.



 $\alpha = 1, T = Id, \Sigma = \sigma^2 Id$ , where  $\sigma^2 \in \{.1, .01, .0025\}$ 

#### What's next?

#### Commentary

Let  $X_1, X_2, \ldots \stackrel{\text{iid}}{\sim} P$  and  $\hat{\mathcal{J}}_n = \hat{\mathcal{J}}(X_1, \ldots, X_n)$ . • If  $\alpha = T = \Sigma = 1$  and  $P = \sum_{m=0}^{\infty} q(1-q)^m \delta_{18^m}$ , where  $q = (2 \cdot 18)^{-1}$ , then  $\mathbb{E} X^4 < \infty$ and almost surely  $\liminf_{n\to\infty} \min\{|J|: J \in \mathcal{J}_n\} = 1.$ • If  $\alpha = T = 1$ ,  $\Sigma < (32 \ln 2)^{-1}$  and P = Exp(1) then  $\lim_{n \to \infty} |\hat{\mathcal{J}}_n| = \infty$  almost surely. This implies that **RESULT** 2 is not easily generalised!

#### 1. 'Limit' result and unbounded support of P

• the possibility of small probability clusters distant from 0, unbounded # of clusters • no chance of convergence in Hausdorff metric, perhaps only  $d_P$ 

#### 2. Prior on the covariance structure

• we may put Wishart distribution on covariance parameter • preliminary computations for induced partitions give

 $\Delta'(\mathcal{A}) = -\frac{1}{2} \sum p_A \ln \det \left( \operatorname{Var}(X \mid X \in A) \right) - \sum p_A \ln p_A$ 

• more difficult to relate induced partitions to the MAP

available details The on arXiv and soon in Bayesian Analysis