



# Communications in Statistics—Simulation and Computation®

ISSN: 0361-0918 (Print) 1532-4141 (Online) Journal homepage: [www.tandfonline.com/journals/lssp20](http://www.tandfonline.com/journals/lssp20)

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Stephen G. Walker

To cite this article: Stephen G. Walker (2007) Sampling the Dirichlet Mixture Model with Slices, *Communications in Statistics—Simulation and Computation®*, 36:1, 45-54, DOI: [10.1080/03610910601096262](https://doi.org/10.1080/03610910601096262)

To link to this article: <https://doi.org/10.1080/03610910601096262>



Published online: 29 May 2007.



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## Inference

# Sampling the Dirichlet Mixture Model with Slices

STEPHEN G. WALKER

Institute of Mathematics, Statistics, and Actuarial Science,  
University of Kent, Canterbury, Kent, UK

*We provide a new approach to the sampling of the well known mixture of Dirichlet process model. Recent attention has focused on retention of the random distribution function in the model, but sampling algorithms have then suffered from the countably infinite representation these distributions have. The key to the algorithm detailed in this article, which also keeps the random distribution functions, is the introduction of a latent variable which allows a finite number, which is known, of objects to be sampled within each iteration of a Gibbs sampler.*

**Keywords** Bayesian nonparametrics; Density estimation; Dirichlet process; Gibbs sampler; Slice sampling.

**Mathematics Subject Classification** Primary 62G99, 62F15; Secondary 65C60.

### 1. Introduction

The aim of this article is to introduce a new method for sampling the well known and widely used mixture of Dirichlet process (MDP) model. There have been a number of recent contributions to the literature on this problem, notably Ishwaran and Zarepour (2000) and Papaspiliopoulos and Roberts (2005). These papers have been concerned with sampling the MDP model while retaining the random distribution functions.

The issue and the causes of the complexities is the countably infiniteness of the discrete masses from the random distribution functions chosen from the Dirichlet process prior. Ishwaran and Zarepour (2000) circumvent this with an approximate method based on a truncation of the distributions. Motivated by the work of Ishwaran and Zarepour (2000) and Papaspiliopoulos and Roberts (2005) proposed an exact algorithm based on the notion of retrospective sampling. However, the algorithm itself becomes non trivial when applied to the MDP model, and involves setting up a detailed balance criterion with connecting proposal moves

Received May 5, 2006; Accepted May 31, 2006

Address correspondence to Stephen G. Walker, Institute of Mathematics, Statistics, and Actuarial Science, University of Kent, Canterbury, Kent CT2 7NZ, UK; E-mail: s.g.walker@kent.ac.uk

(Green, 1995). On the other hand, we find a simple trick, based on the slice sampling schemes (Damien et al., 1999), which deals with the infiniteness. The introduction of latent variables makes finite the part of the random distribution function required to iterate through a Gibbs sampler. Moreover, all the conditional distributions are easy to sample and no accept/reject methods are needed.

The first sampler for the MDP model, based on a Gibbs sampler, was given in the PhD Thesis of Escobar (1988, 1994). Alternative approaches have been proposed by MacEachern (1994) and co-authors; for example, MacEachern and Müller (1998). A recent survey is given in MacEachern (1998), and other papers in the book of Dey et al. (1998) and by Müller and Quintana (2004). Richardson and Green (1997) provide a comparison with more traditional mixture models and Neal (2000) also discusses ideas for sampling the MDP model.

Recently, Ishwaran and James (2001) developed a Gibbs sampling scheme involving more general stick-breaking priors, which is a direct extension of the Escobar (1988) approach. Escobar's Gibbs sampler makes use of the Pólya-urn sampling scheme (Blackwell and MacQueen, 1973) and the idea of using the Pólya-urn scheme is connected with the procedure of integrating out of the model the random distribution function from the Dirichlet process. Recent attempts have avoided this step and retained the random distribution functions in the algorithms, notably Ishwaran and Zarepour (2001) and Papaspiliopoulos and Roberts (2005).

In Sec. 2, we describe the Dirichlet process mixture model and describe the latent variables of use to the sampling strategy. In Sec. 3 we will write down the algorithm for the Gibbs sampler and Sec. 4 contains a couple of illustrative examples. Finally, Sec. 5 concludes with a brief discussion.

## 2. The Dirichlet Process Model

Let  $D(c, P_0)$  denote a Dirichlet process prior (Ferguson, 1973) with scale parameter  $c > 0$  and prior probability measure  $P_0$ . So, for example,  $E(P) = P_0$  and

$$\text{Var}(P(A)) = \frac{P_0(A)\{1 - P_0(A)\}}{c + 1}$$

for all appropriate sets  $A$ . The posterior distribution of  $P$  given  $n$  independent and identically distributed samples from  $P$  is also a Dirichlet process with new parameters  $c + n$  and

$$\frac{cP_0 + nP_n}{c + n},$$

where  $P_n$  is the empirical distribution function. However, we will not be needing this particular result.

It is well known that a random probability measure  $P$  can be chosen from  $D(c, P_0)$  via the following sampling scheme, attributable to Sethuraman and Tiwari (1982), see also Sethuraman (1994), and involving the so-called stick-breaking prior (see, for example, Connor and Mosimann, 1969; Freedman, 1963). Take  $v_1, v_2, \dots$  to be independent and identically distributed beta(1,  $c$ ) variables and take  $\theta_1, \theta_2, \dots$

to be independent and identically distributed from  $P_0$ , which we will assume has density  $g_0$  with respect to the Lebesgue measure. Then define

$$P = \sum_{j=1}^{\infty} w_j \delta_{\theta_j},$$

where  $w_1 = v_1$  and for  $j > 1$ ,

$$w_j = v_j \prod_{l < j} (1 - v_l).$$

Here  $\delta_\theta$  denotes the measure with a point mass of 1 at  $\theta$ . The weights are obtained via what is known as a stick-breaking procedure. Ishwaran and James (2001) consider a more general model with the  $v_j \sim \text{beta}(a_j, b_j)$  and show that the sum of weights is 1 almost surely when

$$\sum_{j=1}^{\infty} \log(1 + a_j/b_j) = +\infty.$$

While we work with the  $v$ 's which lead to the Dirichlet process, our algorithm for sampling the MDP model can be extended to cover other stick-breaking prior distributions in a simple way. This will be elaborated on later in the article.

The MDP model is based on the idea of constructing absolutely continuous random distribution functions and was first considered in Lo (1984). The random distribution function chosen from a Dirichlet process is almost surely discrete (Blackwell, 1973). Consequently, consider the random density function

$$f_P(y) = \int N(y | \theta) dP(\theta).$$

Here,  $N(y | \theta)$  denotes a conditional density function, which will typically be a normal distribution and the parameters of which are represented by  $\theta$ . So in the normal case  $\theta = (\mu, \sigma^2)$ . Given the form for  $P$ , we can write

$$f_{w,\theta}(y) = \sum_j w_j N(y | \theta_j).$$

The prior distributions for the  $w$  and  $\theta$  have been given earlier.

Our attempt to estimate the model, via Gibbs sampling ideas, is to introduce a latent variable  $u$  such that the joint density with of  $(y, u)$  given  $(w, \theta)$  is given by

$$f_{w,\theta}(y, u) = \sum_j \mathbf{1}(u < w_j) N(y | \theta_j).$$

Clearly, integrating over  $u$  with respect to the Lebesgue measure returns us the desired density  $f_{w,\theta}(y)$ . Hence, the joint density exists and so there will also exist a marginal density for  $u$ . Alternatively, we can write

$$f_{w,\theta}(y, u) = \sum_{j=1}^{\infty} w_j U(u | 0, w_j) N(y | \theta_j)$$

and so with probability  $w_j$ ,  $y$ , and  $u$  are independent and are, respectively, normal and uniform distributed. Hence, the marginal density for  $u$  is given by

$$f_w(u) = \sum_{j=1}^{\infty} w_j U(u | 0, w_j) = \sum_{j=1}^{\infty} \mathbf{1}(u < w_j).$$

If we let

$$A_w(u) = \{j : w_j > u\}$$

then we can equally write

$$f_{w,\theta}(y, u) = \sum_{j \in A_w(u)} N(y | \theta_j).$$

Note, it is quite clear that  $A_w(u)$  is a finite set for all  $u > 0$ . The conditional density of  $y$  given  $u$  is given by

$$f_{w,\theta}(y | u) = \frac{1}{f_w(u)} \sum_{j \in A_w(u)} N(y | \theta_j),$$

where  $f_w(u) = \sum_j \mathbf{1}(u < w_j)$  is the marginal density for  $u$ , being defined on  $(0, w^*)$  where  $w^*$  is the largest  $w_j$ .

The usefulness of the latent variable  $u$  will become clear later on. A brief comment here is that the move from an infinite sum to a finite sum, given  $u$ , is going to make a lot of difference when sampling is involved.

So, given  $u$ , we have a finite mixture model with equal weights, all equal to  $1/f_w(u)$ . We can now introduce a further indicator latent variable which will identify the component of the mixture from which  $y$  is to be taken. Therefore, consider the joint density

$$f_{w,\theta}(y, \delta = k, u) = N(y | \theta_k) \mathbf{1}(k \in A(u)).$$

The complete data likelihood based on a sample of size  $n$  is easily seen to be

$$l_{w,\theta}(\{y_i, u_i, \delta_i = k_i\}_{i=1}^n) = \prod_{i=1}^n N(y_i | \theta_{k_i}) \mathbf{1}(u_i < w_{k_i}).$$

As has been mentioned, we already know the prior distributions for the  $w$  and  $\theta$ . Though as it happens, we will use the  $v$ 's rather than the  $w$ 's when it comes to sampling.

### 3. The Sampling Algorithm

In order to implement a Gibbs sampler we require the set of full conditional density functions. For the infinite collection of variables  $v$  and  $\theta$ , it would seem that we would need to sample the entire set. But this is not required. We only need to sample a finite set of them at each stage in order to progress to the next iteration. All un-sampled  $v_j$ 's and  $\theta_j$ 's will be independent samples from the priors; that

is  $\text{beta}(1, c)$  and  $g_0$ , respectively. Let us proceed to consider the full conditional densities; listed **A–E**.

**A.** We will start with the  $u_i$ 's. These are easy to find and are the uniform distributions on the interval

$$(0, w_{k_i}).$$

**B.** Next we have  $\theta_j$ , and this is easily seen to be the density function given up to a constant of proportionality by

$$f(\theta_j | \dots) \propto g_0(\theta_j) \prod_{k_i=j} N(y_i | \theta_j).$$

If there are no  $k_i$  equal to  $j$  then  $f(\theta_j | \dots) = g_0(\theta_j)$ .

**C.** Slightly harder, but quite doable, is the sampling of the  $v_j$ 's. For the joint full conditional density we have

$$f(v | \dots) \propto \pi(v) \prod_{i=1}^n \mathbf{1}(w_{k_i} > u_i),$$

where  $\pi(v)$  denotes the collection of independent beta variables, and we have already given the relation between the  $w_j$ 's and the  $v_j$ 's. Hence,

$$f(v | \dots) \propto \pi(v) \prod_{i=1}^n \mathbf{1}\left(v_{k_i} \prod_{l < k_i} (1 - v_l) > u_i\right).$$

It is quite evident from this that only the  $v_j$ 's for  $j \leq k^*$ , where  $k^*$  is the maximum of  $\{k_1, \dots, k_n\}$ , will be affected; that is, for  $j > k^*$ , we have  $f(v_j | \dots) = \text{beta}(1, c)$ . For  $j \leq k^*$  we have

$$f(v_j | v_{-j}, \dots) \propto \text{beta}(v_j | 1, c) \mathbf{1}(\alpha_j < v_j < \beta_j),$$

where

$$\alpha_j = \max_{k_i=j} \left\{ \frac{u_i}{\prod_{l < j} (1 - v_l)} \right\}$$

and

$$\beta_j = 1 - \max_{k_i > j} \left\{ \frac{u_i}{v_{k_i} \prod_{l < k_i, l \neq j} (1 - v_l)} \right\}.$$

Then the distribution function, on  $\alpha_j < v_j < \beta_j$ , is given by

$$F(v_j) = \frac{(1 - \alpha_j)^c - (1 - v_j)^c}{(1 - \alpha_j)^c - (1 - \beta_j)^c}$$

and so a sample can be taken via the inverse cdf technique. Clearly, it is now evident that this approach covers more general stick-breaking models; it is no more difficult to sample a truncated beta variable when we have  $v_j \sim \text{beta}(a_j, b_j)$  as the priors.

**D.** We now discuss the sampling of the indicator variables. We clearly have

$$\text{pr}(\delta_i = k \mid \dots) \propto \mathbf{1}(k \in A_w(u_i)) N(y_i \mid \theta_k).$$

Clearly,  $A_w(u_i)$  is not empty; at least  $k_i \in A_w(u_i)$ .

Before providing details on how to sample this, we mention that without the latent variables  $u_i$ , the possible choices of  $\delta_i$  would be infinite and problems then arise with the normalizing constant. Papaspiliopoulos and Roberts (2005) attempted to circumvent the problem via retrospective sampling and the use of a detailed-balance criterion, which is non trivial. Our approach is quite easy to implement. The choice of  $\delta_i$  is from a finite set, which is  $\{k : w_k > u_i\}$ . So we sample as many of the  $w_k$ 's until we are sure that we have all the  $w_k > u_i$ . How do we know this? We are sure there can be no further  $k > k^i$  for which  $w_k > u_i$  when we have  $k^i$  such that

$$\sum_{j=1}^{k^i} w_j > 1 - u_i.$$

So, to cover all the  $i$ 's, we find the smallest  $k^*$  such that

$$\sum_{j=1}^{k^*} w_j > 1 - u^*,$$

where  $u^* = \min\{u_1, \dots, u_n\}$ . Hence, we now know how many of the  $w_k$ 's we need to sample in order for the chain to proceed; it is  $\{w_1, \dots, w_{k^*}\}$ . It is that  $k^*$  will be necessary to find to implement the algorithm. One needs to know how many of the  $w_j$  are larger than  $u$  and it is only at  $k^*$  that one knows for sure that all have been found. Hence,  $k^*$  is not a loose approximation; it is an exact piece of information.

For the prior model it is that,

$$k^* \sim 1 + \text{Poisson}(-c \log u^*).$$

See Muliere and Tardella (1998).

**E.** We can incorporate a prior on  $c$ , say  $\pi(c)$ . We will sample  $f(c, w, \theta \mid y, u, \delta)$  as a block, and will sample this in two stages; first by sampling from  $f(c \mid y, u, \delta)$  and then  $f(w, \theta \mid c, y, u, \delta)$ . We have already described how to sample from the latter of these. For the former, it is equivalent to the full conditional density that would arise from the marginal model, that is the one in which the random distribution functions are removed from the model. Therefore, as is well known, it is only the  $\delta$  and the sample size that provides information about  $c$ . To elaborate on this, the conditional distribution of  $c$  depends only on the number of clusters; that is, the number of distinct  $k_i$ 's, call this  $d$ , and that

$$f(c \mid d, n) \propto c^d \Gamma(c) \pi(c) / \Gamma(c + n),$$

where  $\Gamma(\cdot)$  denotes the usual gamma function. A nice way to sample from this is given in Escobar and West (1995) when  $\pi(c)$  is a gamma distribution.

Hence, all the conditional densities are easy to sample and the Markov chain we have constructed is automatic. It requires no tuning nor retrospective steps.

For density estimation we would like to sample from the predictive distribution of

$$f(y_{n+1} | y_1, \dots, y_n).$$

At each iteration we have  $(w_j, \theta_j)$  and we sample a  $\theta_j$  using the weights. The idea is to sample a uniform random variable  $r$  from the unit interval and to take that  $\theta_j$  for which  $w_{j-1} < r < w_j$ , with  $w_0 = 0$ . If more weights are required than currently exist then it is straightforward to sample more as we know the additional  $v_j$ 's for  $j > k^*$  are independent and identically distributed from  $\text{beta}(1, c)$  and the additional  $\theta_j$ 's are independent and identically distributed from  $g_0$ . Having taken  $\theta_j$ , we draw  $y_{n+1}$  from  $N(\cdot | \theta_j)$ .

#### 4. Illustration

Here we present a normal example in which  $\theta = (\mu, \sigma^2)$  and we will take  $\lambda = \sigma^{-2}$ . The prior for the  $\mu_j$ 's will be independent  $N(0, 1/s)$  and the prior for the  $\lambda_j$ 's will be independent  $Ga(\epsilon, \epsilon)$ . To complement Sec. 3 we now provide the conditional distributions for  $\mu_j$  and  $\lambda_j$ . We have

$$f(\mu_j | \dots) = N\left(\frac{\xi_j \lambda_j}{m_j \lambda_j + s}, \frac{1}{m_j \lambda_j + s}\right),$$

where

$$\xi_j = \sum_{k_i=j} y_i$$

and

$$m_j = \sum_{k_i=j} 1.$$

We also have

$$f(\lambda_j | \dots) = Ga(\epsilon + m_j/2, \epsilon + d_j/2),$$

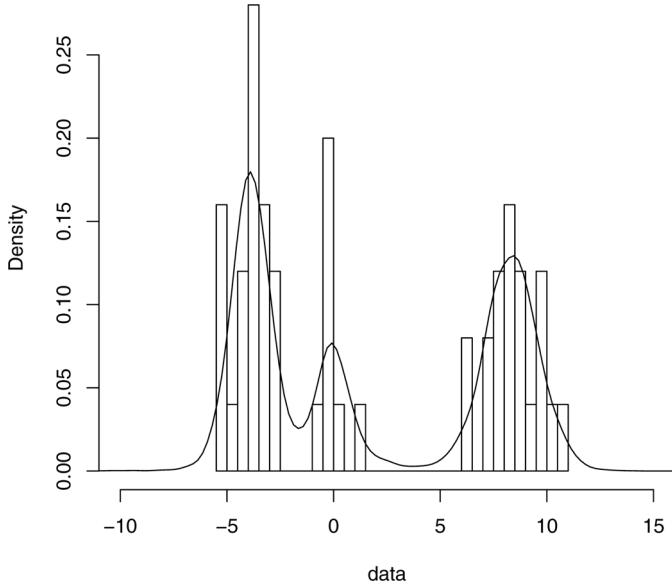
where

$$d_j = \sum_{k_i=j} (y_i - \theta_j)^2.$$

In the simulated data set example that follows, the code was written using scilab, which is freely downloadable from the internet.

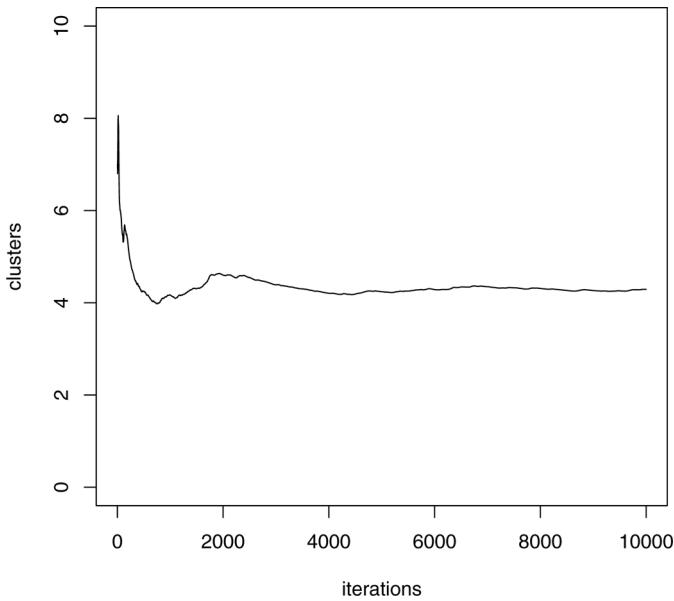
We sampled 50 random variables independently from the mixture of normal distributions given by

$$f(y) = \frac{1}{3}N(y | -4, 1) + \frac{1}{3}N(y | 0, 1) + \frac{1}{3}N(y | 8, 1).$$



**Figure 1.** Histogram of data and density estimate of predictive density for  $1/3N(-4, 1) + 1/3N(0, 1) + 1/3N(8, 1)$ .

Choosing non informative specifications, we took  $\epsilon = 0.5$ ,  $s = 0.1$  and the gamma prior for  $c$  to be  $Ga(0.1, 0.1)$ , the Gibbs sampler was run for 20,000 iterations and at each iteration from 10,000 onwards a predictive sample  $y_{n+1}$  was taken. A histogram of the 50 data points with the density estimator based on the 10,000 samples of  $y_{n+1}$



**Figure 2.** Running average for the number of clusters up to iteration 10,000.

is provided in Fig. 1. The density estimator was obtained using the R density routine with bandwidth set to 0.3.

Figure 2 presents the running average for the number of clusters sampled at each iteration. So it is clear that 10,000 samples is good enough for the chain to reach stationarity and hence the samples from 10,000 onwards can be taken as coming from the predictive distribution.

## 5. Discussion

We have provided a simple and fast way to sample the MDP model. The key is the introduction of the latent variables which truncate the weights of the random Dirichlet distributions. It is a highly simple piece of code to write and is direct in the sense that no accept/reject sampling nor retrospective sampling is required. It is also remarkably quick to run. It improves on current approaches in the following way: we know exactly how many of the  $w_j$ 's and  $\theta_j$ 's we need to sample at each iteration—it is  $k^*$ . This fundamental result eludes the alternative approaches.

Retaining the random distribution function is useful as it removes the dependence between the  $\theta_{k_i}$ 's which exist in the Pólya-urn model. However, retaining the random distributions leads to problems with the countably infinite representation. In this article we deal with it by introducing a latent variable which makes the representation finite for the purposes of proceeding with the sampling and allowing sampling from the predictive distribution. The sampling of the latent variable given the other variables is a uniform distribution.

In the non conjugate case, that is when  $N(y | \theta)$  and  $g_0(\theta)$  form a non-conjugate pair and perhaps difficult to sample, then a possible useful solution is again provided by the latent variable ideas presented in Damien et al. (1999, Secs. 4 and 5).

## Acknowledgment

The author is an EPSRC Advanced Research Fellow and the article was written during a visit to the University of Turin funded by ICER.

## References

- Blackwell, D. (1973). The discreteness of Ferguson selections. *Ann. Statist.* 1:356–358.
- Blackwell, D., MacQueen, J. B. (1973). Ferguson distributions via Pólya-urn schemes. *Ann. Statist.* 1:353–355.
- Connor, R. J., Mosimann, J. E. (1969). Concepts of independence for proportions with a generalization of the Dirichlet distribution. *J. Amer. Statist. Assoc.* 64:194–206.
- Damien, P., Wakefield, J. C., Walker, S. G. (1999). Gibbs sampling for Bayesian non-conjugate and hierarchical models by using auxiliary variables. *J. Roy. Statist. Soc., Ser. B* 61:331–344.
- Dey, D., Sinha, D., Müller, P. (1998). *Practical Nonparametric and Semiparametric Bayesian Statistics*. Lecture Notes in Statistics. New York: Springer.
- Escobar, M. D. (1988). Estimating the means of several normal populations by nonparametric estimation of the distribution of the means. Unpublished Ph.D. dissertation, Department of Statistics, Yale University.
- Escobar, M. D. (1994). Estimating normal means with a Dirichlet process prior. *J. Amer. Statist. Assoc.* 89:268–277.

- Escobar, M. D., West, M. (1995). Bayesian density estimation and inference using mixtures. *J. Amer. Statist. Assoc.* 90:577–588.
- Freedman, D. A. (1963). On the asymptotic behaviour of Bayes estimates in the discrete case. *I. Ann. Mathemat. Statist.* 34:1386–1403.
- Ferguson, T. S. (1973). A Bayesian analysis of some nonparametric problems. *Ann. Statist.* 1:209–230.
- Green, P. J. (1995). Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. *Biometrika* 82:711–732.
- Ishwaran, H., Zarepour, M. (2000). Markov chain Monte Carlo in approximate Dirichlet and beta two-parameter process hierarchical models. *Biometrika* 87:371–390.
- Ishwaran, H., James, L. (2001). Gibbs sampling methods for stick-breaking priors. *J. Amer. Statist. Assoc.* 96:161–173.
- Ishwaran, H., Zarepour, M. (2001). Markov chain Monte Carlo in approximate Dirichlet and beta two-parameter process hierarchical models. *Biometrika* 87:371–390.
- Lo, A. Y. (1984). On a class of Bayesian nonparametric estimates I. Density estimates. *Ann. Statist.* 12:351–357.
- MacEachern, S. N. (1994). Estimating normal means with a conjugate style Dirichlet process prior. *Commun. Statist. Simulat. Computat.* 23:727–741.
- MacEachern, S. N. (1998). Computational methods for mixture of Dirichlet process models. In: Dey, D., Müller, P., Sinha, D., eds. *Practical Nonparametric and Semiparametric Bayesian Statistics*. New York: Springer, pp. 23–43.
- MacEachern, S. N., Müller, P. (1998). Estimating mixtures of Dirichlet process models. *J. Computat. Graph. Statist.* 7:223–238.
- Muliere, P., Tardella, L. (1998). Approximating distributions of random functionals of Ferguson-Dirichlet priors. *Canad. J. Statist.* 26:283–297.
- Müller, P., Quintana, F. A. (2004). Nonparametric Bayesian data analysis. *Statist. Sci.* 19:95–110.
- Neal, R. M. (2000). Markov chain sampling methods for Dirichlet process mixture models. *J. Computat. Graph. Statist.* 9:249–265.
- Papaspiliopoulos, O., Roberts, G. O. (2005). Retrospective Markov chain Monte Carlo methods for Dirichlet process hierarchical models. Submitted.
- Richardson, S., Green, P. J. (1997). On Bayesian analysis of mixtures with an unknown number of components. *J. Roy. Statist. Soc., Ser. B* 59:731–792.
- Sethuraman, J. (1994). A constructive definition of Dirichlet priors. *Statistica Sinica* 4:639–650.
- Sethuraman, J., Tiwari, R. (1982). Convergence of Dirichlet measures and the interpretation of their parameter. In: Gupta, S. S., Berger, J. O., eds. *Proceedings of the Third Purdue Symposium on Statistical Decision Theory and Related Topics*. New York: Academic press.