## Appendix

## A.1. Implementing DP Mixtures in R

We introduce some R macros to implement inference in a DP mixture in (3.9). Using Gaussian kernels the DP mixture model becomes

$$
\begin{equation*}
y_{i} \mid G \sim F\left(y_{i}\right)=\int N\left(y_{i} ; \theta_{i}, \sigma\right) d p(G) . \tag{A.10}
\end{equation*}
$$

We will use $f(x)$ to denote the p.d.f. The moel can equivalently be written as a hierarchical model

$$
\begin{equation*}
y_{i}\left|\theta_{i} \sim N\left(\theta_{i}, \sigma\right), \quad \theta_{i}\right| G \sim G \tag{A.11}
\end{equation*}
$$

where $G \sim \operatorname{DP}\left(M, G_{0}\right)$. For the centering measure, we use $G_{0}=N\left(m_{0}, B_{0}\right)$, and we take $m_{0}=0$ and $B_{0}=4$, while the precision parameter is set to $M=1$. We complete the model with a gamma prior for the kernel width, $1 / \sigma^{2} \sim \mathrm{Ga}(a, b)$; in the example below we take $a=b=1$. We implement posterior MCMC simulation using the methods described in $\S 3.3$. The complete R code is available at
http://www.math.utexas.edu/users/pmueller/prog/BNPnotes/
We briefly explain the main steps in the macros. We use the data from the Old Faithful geyser data in R and fix the hyperparameters for the model. The hyperparameters and the data are saved as global variables:

```
## DATA: Old Faithful geyser data
y <- round(faithful$eruptions, digits=2)
n <- length(y)
## hyperparameters
a <- 1; b <- 1 # 1/sig ~ Ga(a,b)
m0<- 0; BO <- 4 # GO = N(m0,BO)
M <- 1
```

Collapsed Gibbs Sampler - Conjugate Models
We first implement the Gibbs sampler from §3.3.1. The algorithm consists of the following steps:
0. Initialization: We initialize $s_{i}$ using (deterministic) hierarchical clustering.

Initialize a plot by plotting a kernel density estimate of $f(y)$.

1. Update $\theta_{i}$ : sample from $p\left(\theta_{i} \mid \boldsymbol{\theta}_{-i}, \sigma, \mathbf{y}\right), i=1, \ldots, n$. See (3.13).
2. Update $\theta_{j}^{\star}$ : sample from $p\left(\theta_{j}^{\star} \mid s_{i}, \sigma, \mathbf{y}\right), j=1, \ldots, k$, as in (3.14).
3. Update $\sigma^{2}$ : sample from $p\left(\sigma^{2} \mid \mathbf{s}, \boldsymbol{\theta}^{\star}, \mathbf{y}\right)$.
4. Generate $f$ : generate $f \sim p(f \mid \boldsymbol{\theta}, \phi, \sigma)$; add $f$ to the plot.

In Step 4 we sample $f$ conditional on the currently imputed values of $\boldsymbol{\theta}, \phi, \sigma$. For plotting it suffices to evaluate $f$ on a grid that is fine enough to get a smooth plot. To sample $f$ (on the grid) we use a minor approximation. Essentially we (i) sample $G \sim p(G \mid \boldsymbol{\theta})$, and (ii) evaluate $F=\int \mathrm{N}(\theta, \sigma) d G(\theta)$. The approximation

