BNPlib: A Nonparametric C++ Library
(part 3)

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https://github.com/poliprojects/BNPlib

Model

DP and DPM models

Having observed the iid sample $\{y_i\}_i$, $i = 1, \ldots, n$:

- Dirichlet process model (discrete):

$$y_i | G \stackrel{\text{iid}}{\sim} G$$
$$G \sim DP(MG_0)$$

- Dirichlet process mixture (**DPM**) model (continuous):

$$y_i | G \stackrel{\text{iid}}{\sim} f_G(\cdot) = \int_{\Theta} f(\cdot | \boldsymbol{\vartheta}) \, G(\mathrm{d}\boldsymbol{\vartheta})$$
$$G \sim DP(MG_0)$$

Equivalent formulations (1)

- (DPM) is equivalent to:

$$y_i | \boldsymbol{\vartheta}_i \overset{\text{ind}}{\sim} f(\cdot | \boldsymbol{\vartheta}_i), \quad i = 1, \ldots, n$$
$$\boldsymbol{\vartheta}_i | G \overset{\text{iid}}{\sim} G, \quad i = 1, \ldots, n$$
$$G \sim DP(MG_0)$$

- State $\forall i$: $\boldsymbol{\vartheta}_i$ latent variables (discrete)

Equivalent formulations (2)

- (DPM) is also equivalent to:

$$y_i | c_i, \phi_1, \ldots, \phi_k \overset{\text{ind}}{\sim} f(\cdot | \phi_{c_i}), \quad i = 1, \ldots, n$$

$$c_i | \mathbf{p} \overset{\text{iid}}{\sim} \sum_{j=1}^{K} p_j \delta_j(\cdot), \quad i = 1, \ldots, n$$

$$\phi_c \overset{\text{iid}}{\sim} G_0, \quad c = 1, \ldots, k$$

$$\mathbf{p} \sim \text{Dir}(M/K, \ldots, M/K)$$

$$K \to +\infty$$

- State $\forall i$: c_i **allocations** to clusters
- State $\forall i$: ϕ_{c_i} **unique values** for each cluster
- Only the finitely many ϕ_c used are kept track of

Case study

- (DPM) with a Normal Normal-InverseGamma (**NNIG**) hierarchy:

$$y_i|\boldsymbol{\vartheta}_i \overset{\text{ind}}{\sim} f(\cdot|\boldsymbol{\vartheta}_i), \quad i = 1, \dots, n$$

$$\boldsymbol{\vartheta}_i|G \overset{\text{iid}}{\sim} G, \quad i = 1, \dots, n$$

$$G \sim DP(MG_0)$$

$$f(y|\boldsymbol{\vartheta}) = N(y|\mu, \sigma^2)$$

$$G_0(\boldsymbol{\vartheta}|\mu_0, \lambda_0, \alpha_0, \beta_0) = N\left(\mu|\mu_0, \frac{\sigma^2}{\lambda_0}\right) \times \text{Inv-Gamma}(\sigma^2|\alpha_0, \beta_0)$$

- Latent variables: $\boldsymbol{\vartheta} = (\mu, \sigma)$
- State $\forall i$: c_i, $\boldsymbol{\phi}_{c_i}$

Algorithms

General structure

```
template<template <class> class Hierarchy,
         class Hypers, class Mixture> class Algorithm

        void step(){
            sample_allocations();
            sample_unique_values();
        }

        void run(){
            initialize();
            unsigned int iter = 0;
            while(iter < maxiter){
                step();
                if(iter >= burnin){
                    save_iteration(iter);
                }
                iter++;
            }
        }
```

Auxiliary classes

- Specific common interface
- `Mixture` → `SimpleMixture`
- `Hypers` → `HypersFixedNNIG`
- `Hierarchy<Hypers>` → `HierarchyNNIG<Hypers>`

Neal8

- Has a vector of m `aux_unique_values`
- `initialize()`
- `sample_allocations()`: for all observations $i = 1, \ldots, n$
  - compute `card[c]` $= n_{-i,c}$ for all clusters $c = 1, \ldots, k$
  - if c_i is a singleton, move ϕ_{c_i} to `aux_unique_values[0]`
  - draw all (other) `aux_unique_values` iid from G_0
  - draw a new value c for c_i according to:

$$\mathbb{P}(c_i = c | \boldsymbol{c}_{-i}, y_i, \boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_h) \propto \begin{cases} \dfrac{n_{-i,c}}{n - 1 + M} f(y_i | \boldsymbol{\phi}_c), & \text{for } 1 \le c \le k^- \\ \dfrac{M/m}{n - 1 + M} f(y_i | \boldsymbol{\phi}_c), & \text{for } k^- + 1 < c \le h \end{cases}$$

  with k^- unique values excluding c_i and $h = k^- + m$
  - update `card` and `allocations` (4 cases)
- `sample_unique_values()`: for all clusters $c = 1, \ldots, k$
  - build `curr_data` that contains all observations in cluster c
  - draw $\boldsymbol{\phi}_c$ from its posterior distribution given `curr_data`

Neal2

- For conjugate models only, e.g. (DPM)+(NNIG)
- `initialize()`
- `sample_allocations()`: for all observations $i = 1, \ldots, n$
  - compute `card[c]` $= n_{-i,c}$ for all clusters $c = 1, \ldots, k$
  - draw a new value c for c_i according to:

If $c = c_j$ for some j: $\mathbb{P}(c_i = c | \boldsymbol{c}_{-i}, y_i, \boldsymbol{\phi}) \propto \dfrac{n_{-i,c}}{n - 1 + M} f(y_i | \boldsymbol{\phi}_c)$

$$\mathbb{P}(c_i \neq c_j \text{ for all } j | \boldsymbol{c}_{-i}, y_i, \boldsymbol{\phi}) \propto \dfrac{M}{n - 1 + M} \int_{\Theta} f(y_i | \boldsymbol{\vartheta}) \, G_0(\mathrm{d}\boldsymbol{\vartheta})$$

  - if the latter, draw a new $\boldsymbol{\phi}_c$ from its posterior given y_i
  - update `card` and `allocations` (4 cases)
- `sample_unique_values()`: for all clusters $c = 1, \ldots, k$
  - build `curr_data` that contains all observations in cluster c
  - draw $\boldsymbol{\phi}_c$ from its posterior distribution given `curr_data`

Applications

Cluster estimation

```
unsigned int cluster_estimate();
```

$$\hat{k} = \arg\min_k \left\| D^{(k)} - \bar{D} \right\|_F^2 = \arg\min_k \sum_{i,j} \left(D_{ij}^{(k)} - \bar{D}_{ij} \right)^2$$

- $D^{(k)}$: dissimilarity matrix at iteration k
- $\bar{D} = \frac{1}{K} \sum_k D^{(k)}$: mean over K iterations

Density estimation

```
void eval_density(const std::vector<double> grid);
```

$$\hat{f}^{(k)}(x) \ = \ \sum_j \frac{n_j^{(k)}}{M+n} f\left(x|\phi_j^{(k)}\right) \ + \ \frac{M}{M+n} m(x)$$

$$\hat{m}(x) = \frac{1}{m} \sum_{h=0}^{m-1} f\left(x|\phi_h\right)$$

$$\implies \hat{f}(x) = \frac{1}{K} \sum_k \hat{f}^{(k)}(x)$$

Results

Oscillations

Number of clusters at single iterations
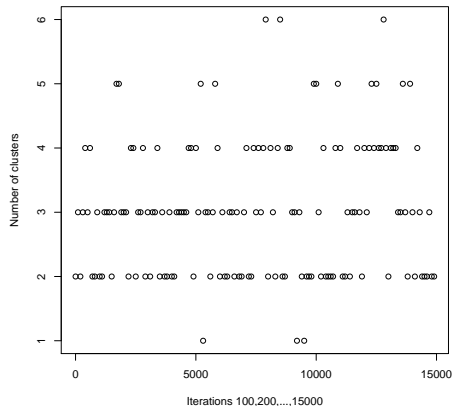
Local density estimates at single iterations
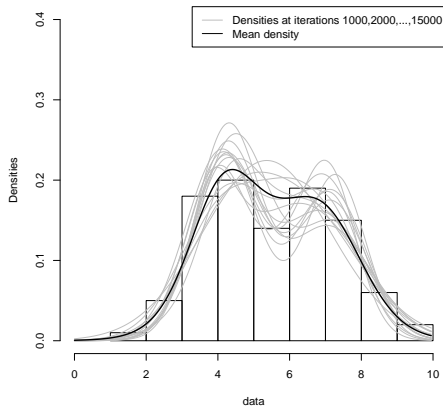
Total mass

Number of clusters as a function of the total mass
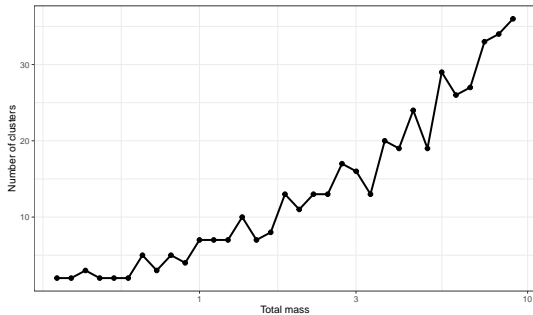
Estimated posterior density

Auxiliary parameters

Estimated posterior density

Density components

Components of the density at the best clustering
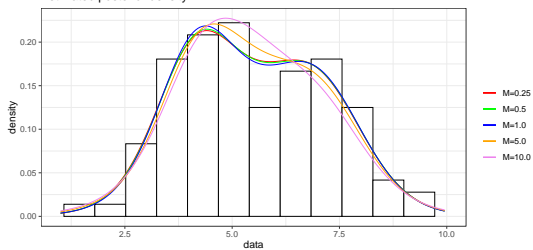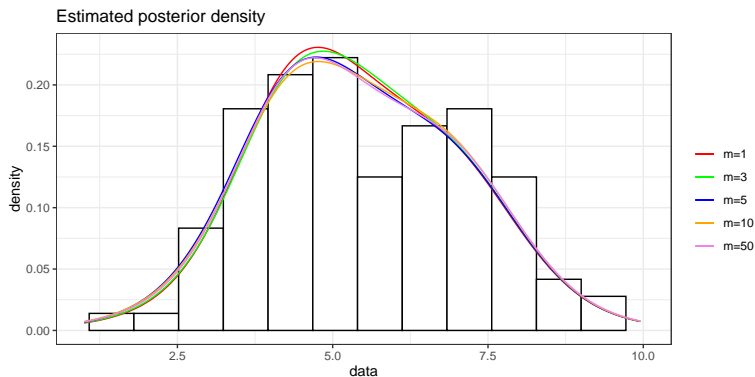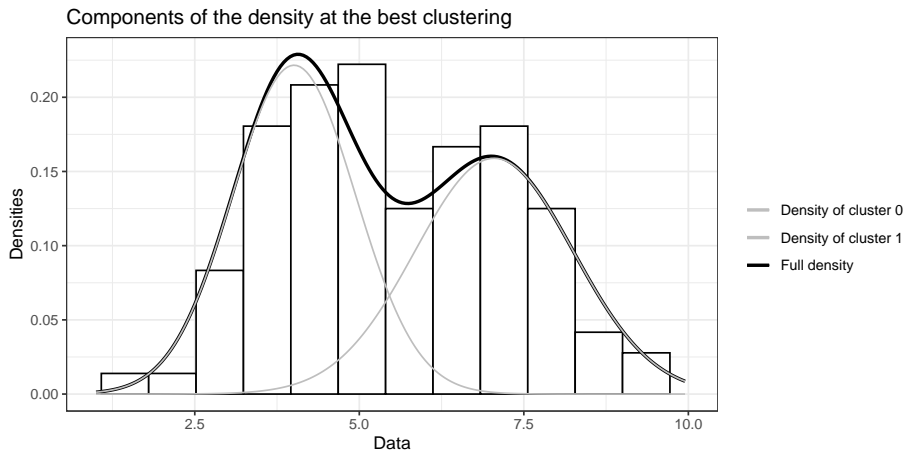
Clustering

Neal2 vs Neal8

Estimated posterior density
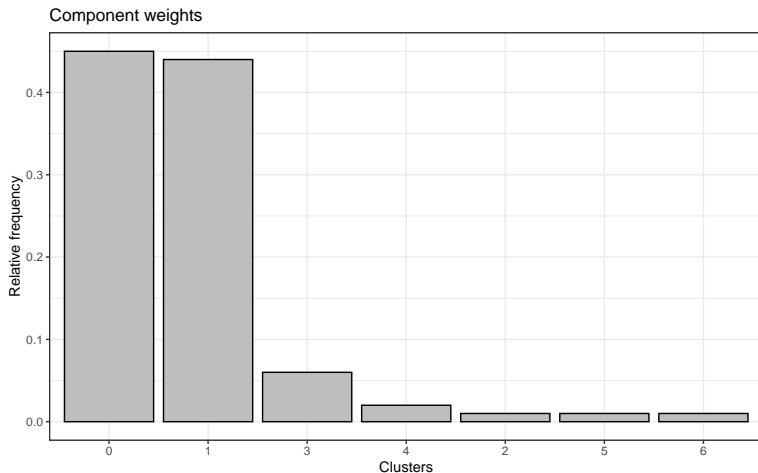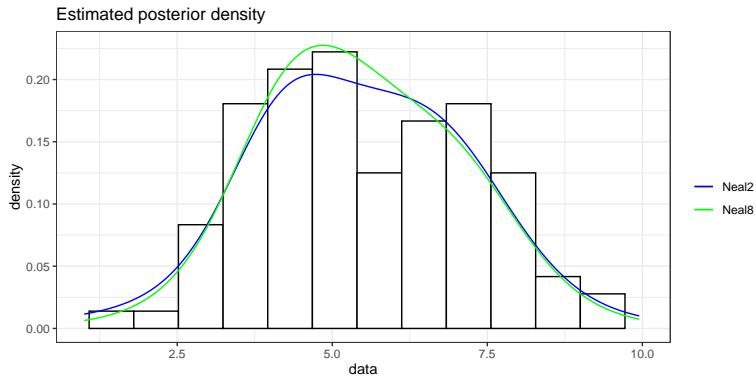
Bibliography

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📕 Neal (2000), *Markov Chain Sampling Methods for Dirichlet Process Mixture Models*

📕 Ishwaran, James (2001), *Gibbs Sampling Methods for Stick-Breaking Priors*

📕 Murphy (2007), *Conjugate Bayesian analysis of the Gaussian distribution*

📕 Protocol Buffers: `https://developers.google.com/protocol-buffers/docs/cpptutorial`

📕 Stan: `http://mc-stan.org/math`

📕 Eigen: `https://eigen.tuxfamily.org/dox`

📕 GitHub codes of Mario Beraha and Riccardo Corradin for similar projects

📕 Course material for Bayesian Statistics: `https://beep.metid.polimi.it/web/2019-20-bayesian-statistics-alessandra-guglielmi-/`