

Title

Subtitle

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<https://github.com/poliprojects/BNPLib>

Non-Parametric statistics

- Goal: density estimation
- **Infinite-dimensional** parameters, e.g. functions

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$$\mathcal{P} : \Omega \rightarrow M(S) \text{ fixed}$$
$$[\omega \mapsto G(\cdot)]$$

- Model name: **BNP model**

Dirichlet Process prior

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

- Parameters: $M > 0$, $G_0 \in M(S)$
- Defining property: $\forall \{B_{1:k}\}$ partition of S ,

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- Discreteness** (stick-breaking): $G(\cdot) = \sum_{k=1}^{+\infty} w_h \delta_{m_h}(\cdot)$
- Conjugacy**: $G | \mathbf{y} \sim DP(MG_0 + \sum_i \delta_{y_i}) \implies$ density estimation

Continuous density estimation

- **Mixtures** (kernel f + mixing distribution G):

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- Model name: **DPM model**
- Equivalent to:

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

- ϑ_i “latent variables” $\forall i = 1, \dots, n$

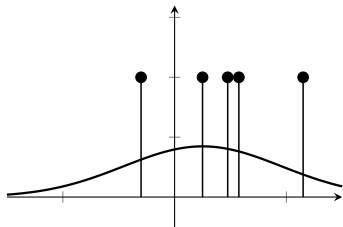
Clustering in the DPM

- Discreteness: the ϑ_i have one of the k **unique values** ϕ_j ($j = 1, \dots, k$)
- $k \simeq M \log(n) \ll n$
- All i s.t. $\vartheta_i = \phi_j$ belong to cluster S_j ($j = 1, \dots, k$), and $n_j = |S_j|$

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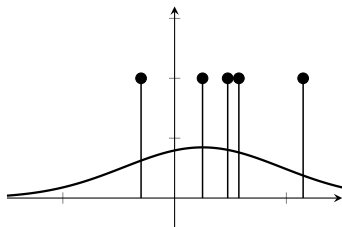
$$\mathcal{L}(\vartheta_i | \boldsymbol{\vartheta}_{-i}) \propto \sum_{j=1}^{k^-} \underset{\uparrow}{n_j^-} \delta_{\underset{\uparrow}{\phi_j^-}}(\vartheta_i) + MG_0(\vartheta_i)$$



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- Conditional posterior for ϑ_i :

$$\mathcal{L}(\vartheta_i | \boldsymbol{\vartheta}_{-i}, y_i) \propto \sum_{j=1}^{k^-} f_{\vartheta}(y_i) \delta_{\phi_j^-}(\vartheta_i) + M r_i G_0(\vartheta_i | y_i)$$

Title

Stuff

Bibliography

-  Muller, Quintana, *Bayesian Nonparametric Data Analysis*
-  Neal (2000), *Markov Chain Sampling Methods for Dirichlet Process Mixture Models*
-  Ishwaran, James (2001), *Gibbs Sampling Methods for Stick-Breaking Priors*