

# Bayesian nonparametric latent feature models

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# Overview

## 1 Introduction

## 2 Dirichlet Process

- Finite mixture model
- Equivalent classes
- Dirichlet Process model
- Chinese Restaurant
- Stick-breaking construction

## 3 Nonparametric latent feature models

- Finite feature model
- Equivalent classes
- Nonparametric latent feature model
- Indian buffet
- Stick-breaking construction

## 4 Applications

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## 4 Applications

# Finite mixture model

- $n$  objects and  $K$  clusters
- Each object  $k = 1, \dots, n$  can belong to only one cluster  $j \in \{1, \dots, K\}$
- Represented by an allocation variable  $c_k \in \{1, \dots, K\}$



# Finite mixture model

- Bayesian approach: Dirichlet-multinomial model

$$\pi_{1:K} \sim \mathcal{D}\left(\frac{\alpha}{K}, \dots, \frac{\alpha}{K}\right)$$

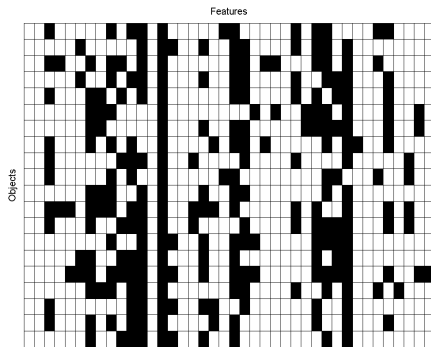
and for  $k = 1, \dots, n$ ,

$$c_k \sim \pi_{1:K}$$

- $K \rightarrow \infty$ : Dirichlet Process

# Finite latent feature model

- $n$  objects and  $K$  features
- Each object  $k$  can have a finite number of latent features
- Represented by a binary vector  $\mathbf{c}_k \in \{0, 1\}^K$



# Finite latent feature model

- Bayesian approach: Prior distribution over a binary matrix of size  $n \times K$
- $K \rightarrow \infty$ : Nonparametric latent feature model

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# Finite mixture model

- Hierarchical model

$$\pi_{1:K} \sim \mathcal{D}\left(\frac{\alpha}{K}, \dots, \frac{\alpha}{K}\right)$$

- For  $j = 1, \dots, K$ ,

$$U_j \sim \mathbb{G}_0$$

- For  $k = 1, \dots, n$ ,

$$c_k \sim \pi_{1:K}$$

$$\mathbf{z}_k | c_k, U_{1:K} \sim f(\cdot | U_{c_k})$$

# Finite mixture model

- Prior distribution

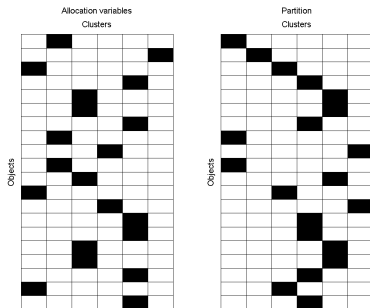
$$\Pr(\pi_{1:K}, U_{1:K}, c_{1:n}) = \Pr(\pi_{1:K}, c_{1:n}) \Pr(U_{1:K})$$

- Can integrate out analytically  $\pi_{1:K}$  (Dirichlet-multinomial distribution)

$$\begin{aligned} \Pr(c_{1:n}) &= \int \Pr(\pi_{1:K}, c_{1:n}) d\pi_{1:K} \\ &= \frac{\Gamma(\alpha) \prod_{j=1}^K \Gamma(n_j + \frac{\alpha}{K})}{\Gamma(\alpha + n) \Gamma(\frac{\alpha}{K})^K} \end{aligned}$$

## Distribution over partitions

- Let  $\Pi_n = \{A_1, \dots, A_{n(\Pi_n)}\}$  be a random partition of  $\{1, \dots, n\}$  and  $\mathcal{P}_n$  the set of partitions of  $\{1, \dots, n\}$
- Ex:  $\Pi_5 = \{\{1, 2, 5\}, \{3\}, \{4\}\}$
- Several different values of  $c_{1:n}$  may induce the same partition
- Ex:  $c_{1:5} = (1, 1, 2, 1, 3)$  and  $c'_{1:5} = (2, 2, 3, 2, 1)$  both induce the same partition  $\Pi_5 = \{\{1, 2, 4\}, \{3\}, \{5\}\}$
- Let  $\Pi_n(c_{1:n})$  be the partition of  $\{1, \dots, n\}$  induced by the equivalence relationship  $i \leftrightarrow j \iff c_i = c_j$



# Distribution over partitions

- We have

$$\Pr(\Pi_n(c_{1:n})) = \frac{K!}{(K - n(\Pi_n))!} \Pr(c_{1:n})$$

for all  $\Pi_n \in \mathcal{P}_K$  where  $\mathcal{P}_K = \{\Pi_n \in \mathcal{P}_n | n(\Pi_n) \leq K\}$

- and thus for the Dirichlet-multinomial distribution

$$\Pr(\Pi_n) = \frac{K!}{(K - n(\Pi_n))!} \frac{\Gamma(\alpha) \prod_{j=1}^K \Gamma(n_j + \frac{\alpha}{K})}{\Gamma(\alpha + n) \Gamma(\frac{\alpha}{K})^K}$$

# Dirichlet Process

- Limit when  $K \rightarrow \infty$  of the finite model

$$\Pr(\Pi_n) = \frac{K!}{(K - n(\Pi_n))!} \frac{\Gamma(\alpha) \prod_{j=1}^K \Gamma(n_j + \frac{\alpha}{K})}{\Gamma(\alpha + n) \Gamma(\frac{\alpha}{K})^K}$$

- is given by

$$\Pr(\Pi_n) = \frac{\alpha^{n(\Pi_n)} \prod_{j=1}^{n(\Pi_n)} \Gamma(n_j)}{\prod_{i=1}^n (\alpha + i - 1)}$$

# Dirichlet Process

- Connexion to the usual formulation

$$\mathbb{G} \sim DP(\alpha, \mathbb{G}_0)$$

for  $k = 1, \dots, n$

$$\theta_k | \mathbb{G} \sim \mathbb{G}$$

- Let  $\Pi_n(\theta_1, \dots, \theta_n)$  be the partition of  $\{1, \dots, n\}$  induced by the equivalence relationship  $i \leftrightarrow j \iff \theta_i = \theta_j$  and  $U_1, \dots, U_{n(\Pi_n)}$  be the different values taken by  $\theta_1, \dots, \theta_n$
- When integrating out the unknown distribution  $\mathbb{G}$

$$\Pr(\theta_1, \dots, \theta_n) = \Pr(\Pi_n(\theta_1, \dots, \theta_n)) \prod_{j=1}^{n(\Pi_n)} \mathbb{G}_0(U_j)$$

# Chinese Restaurant

- Let  $\Pi_{-k}$  be the partition obtained by removing item  $k$  from  $\Pi_n$
- Conditional association probability of item  $k$  is

$$\frac{\Pr(\Pi_n)}{\Pr(\Pi_{-k})}$$

- Item  $k$  is associated to an existing cluster  $j = 1, \dots, n(\Pi_{-k})$  with probability

$$\frac{n_{j,-k}}{n-1+\alpha}$$

and to a new cluster with probability

$$\frac{\alpha}{n-1+\alpha}$$

## Stick-breaking representation

- Let  $\Pi_1, \Pi_2, \dots$  be the successive partitions obtained with sequential CRP updates
- Ex:  $\Pi_1 = \{\{1\}\}$ ,  $\Pi_2 = \{\{1\}, \{2\}\}$ ,  $\Pi_3 = \{\{1, 3\}, \{2\}\}$ ,  
 $\Pi_4 = \{\{1, 3\}, \{2\}, \{4\}\}, \dots$
- Let  $n_{j,t}$  the size of cluster  $j$  in  $\Pi_t$ , where the clusters are numbered in order of appearance
- Let  $\lim_{t \rightarrow \infty} \frac{n_{j,t}}{t} = \pi_j$ . We have

$$\pi_j = \beta_j \prod_{i=1}^{j-1} (1 - \beta_i)$$

where

$$\beta_j \sim \mathcal{B}(1, \alpha)$$

- Stick-breaking construction or residual allocation model



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# Finite feature model

- Assume the following model
- For each feature  $j = 1, \dots, K$ ,

$$\pi_j \sim \mathcal{B}\left(\frac{\alpha}{K}, 1\right)$$

- For each object  $k$  and each feature  $j$

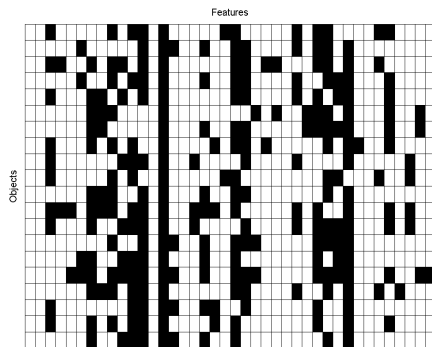
$$c_{k,j} \sim \text{Ber}(\pi_j)$$

# Finite feature model

- Integrating out  $\pi_{1:K}$

$$\Pr(c_{1:n}) = \prod_{j=1}^K \frac{\frac{\alpha}{K} \Gamma(m_j + \frac{\alpha}{K}) \Gamma(n - m_j + 1)}{\Gamma(n + 1 + \frac{\alpha}{K})}$$

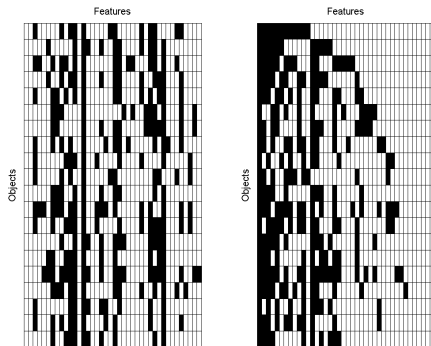
- Invariant to permutation of objects/features



## Equivalent classes

- Distribution over binary matrix is invariant with respect to permutations of columns
- Left-ordered form

$$\Pr(\xi(\mathbf{c}_{1:n})) = \frac{K!}{\prod_{h=0}^{2^n-1} K_h!} \prod_{j=1}^K \frac{\frac{\alpha}{K} \Gamma(m_j + \frac{\alpha}{K}) \Gamma(n - m_j + 1)}{\Gamma(n + 1 + \frac{\alpha}{K})}$$



# Nonparametric latent feature model

- Limit when  $K \rightarrow \infty$  of the finite model

$$\Pr(\xi(\mathbf{c}_{1:n})) = \frac{K!}{\prod_{h=0}^{2^n-1} K_h!} \prod_{j=1}^K \frac{\frac{\alpha}{K} \Gamma(m_j + \frac{\alpha}{K}) \Gamma(n - m_j + 1)}{\Gamma(n + 1 + \frac{\alpha}{K})}$$

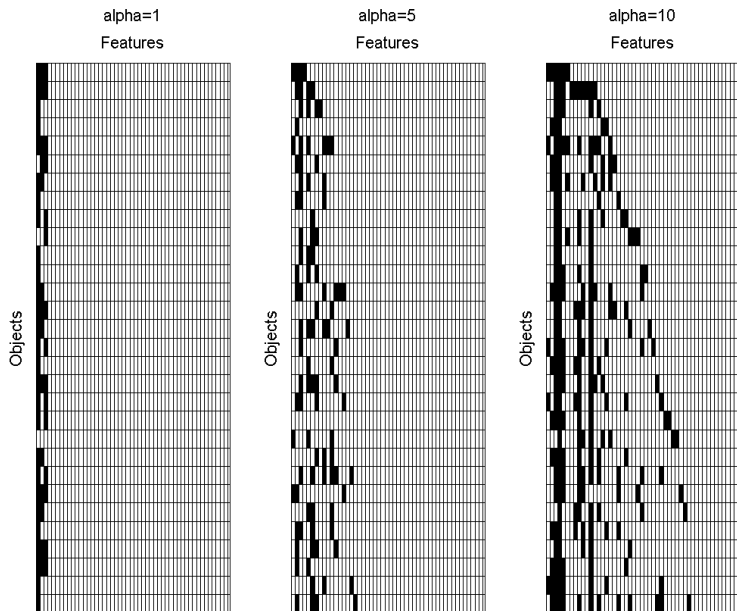
is given by

$$\Pr(\xi(\mathbf{c}_{1:n})) = \frac{K^+}{\prod_{h=1}^{2^n-1} K_h!} \exp(-\alpha H_n) \prod_{j=1}^{K^+} \frac{(n - m_j)! (m_j - 1)!}{n!}$$

# Indian Buffet

- Buffet with infinite number of dishes
- First customer samples  $\text{Poisson}(\alpha)$  dishes
- $k^{\text{eme}}$  customer takes each dish with probability  $m_j/k$  and tries  $\text{Poisson}(\alpha/k)$  new dishes
- Caution: Not in left-ordered form!

# Indian Buffet



# Properties

- Total number of different features  $K^+$  follows  $\text{Poisson}(\alpha(\sum_{k=1}^n \frac{1}{k}))$
- Number of features possessed by each object follows  $\text{Poisson}(\alpha)$
- Total number of entries in the matrix follows  $\text{Poisson}(n\alpha)$

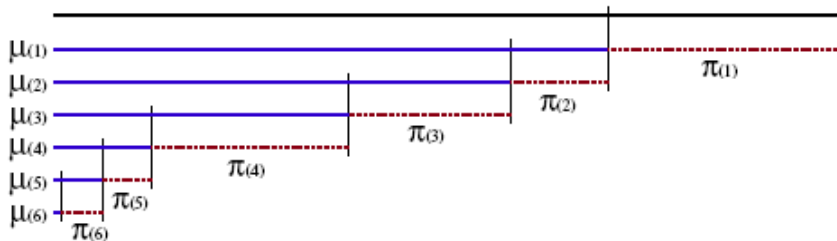


## Stick-breaking construction

- Let  $\pi_{(1)} > \pi_{(2)} > \dots > \pi_{(K)}$  be a decreasing ordering of  $\pi_{1:K}$  where  $\pi_k \sim \mathcal{B}(\frac{\alpha}{K}, 1)$
- Limit when  $K \rightarrow \infty$ : stick-breaking construction

$$\beta_{(k)} \sim \mathcal{B}(\alpha, 1) \text{ and } \pi_{(k)} = \pi_{(k-1)}\beta_{(k)}$$

- DP: stick lengths sum to one and are not decreasing (only in average)
- IBP: stick lengths does not sum to one and are decreasing



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# Applications

- Choice behaviour
- Protein interaction screens
- Structure of causal graphs


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