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# Supplementary material: a hybrid sampler for Poisson-Kingman mixture models

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## 1 Pseudocode

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**Algorithm 1** HybridSampler $\sigma$ -PK $\left(K, V, \mathbf{c}, \{X_i\}_{i \in [n]}, \{Y_c^*\}_{c \in \Pi_n}, \{\tilde{J}_c\}_{c \in \Pi_n}, H_0, M\right)$

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for  $t = 2 \rightarrow iter$  do
  Update  $v^{(t)}$ : Slice sample  $\tilde{\mathbb{P}}(V \in dv \mid \text{rest})$ 
  Update  $s_i^{(t)}$  for  $i = 1, \dots, k$ : Slice sample  $\tilde{\mathbb{P}}(\tilde{J}_i \in ds_i \mid \text{rest})$ 
  Update  $\pi^{(t)}, \left\{y_c^{*(t)}\right\}_{c \in \pi}, \left\{s_c^{(t)}\right\}_{c \in \pi}$ : AddTable&ReUse $\left(V, \Pi_n, M, \{X_i\}_{i \in [n]}, \{Y_c^*\}_{c \in \Pi_n}, \{\tilde{J}_c\}_{c \in \Pi_n}, H_0 \mid \text{rest}\right)$ 
end for

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**Algorithm 2** HybridSampler-MH- $\sigma$ PK $\left(K, V, \mathbf{c}, \{X_i\}_{i \in [n]}, \{Y_c^*\}_{c \in \Pi_n}, \{\tilde{J}_c\}_{c \in \Pi_n}, H_0, M\right)$

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for  $t = 2 \rightarrow iter$  do
  Update  $s_i^{(t)}$  for  $i = 1, \dots, k$ : Slice sample  $\tilde{\mathbb{P}}(\tilde{J}_i \in ds_i \mid \text{rest})$ 
  Update  $v^{(t)}$ : MH step for  $\tilde{\mathbb{P}}(V \in dv \mid \text{rest})$  with independent proposal Stablernd $(\sigma)$  or ExpTiltStablernd $(\lambda, \sigma)$ .
  Update  $\pi^{(t)}, \left\{y_c^{*(t)}\right\}_{c \in \pi}, \left\{s_c^{(t)}\right\}_{c \in \pi}$ : AddTable&ReUse $\left(V, \Pi_n, M, \{X_i\}_{i \in [n]}, \{Y_c^*\}_{c \in \Pi_n}, \{\tilde{J}_c\}_{c \in \Pi_n}, H_0 \mid \text{rest}\right)$ 
end for

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**Algorithm 3** AddTable&ReUse( $V, \Pi_n, M, \{X_i\}_{i \in [n]}, \{Y_c^*\}_{c \in \Pi_n}, \{\tilde{J}_c\}_{c \in \Pi_n}, H_0 \mid \text{rest}$ )

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Let  $c \in \Pi_n$  be such that  $i \in c$   
 $c \leftarrow c \setminus \{i\}$   
**if**  $c = \emptyset$  **then**  
     $k \sim \text{UniformDiscrete}(\frac{1}{M})$   
     $Y_k^e \leftarrow Y_c^*$   
     $\Pi_n \leftarrow \Pi_n \setminus \{c\}$   
     $V \leftarrow V + \tilde{J}_c$   $\triangleright$  Add back the discarded table size to the surplus  
**end if**  
Set  $c'$  according to  $\mathbb{P}(c_i = c \mid \mathbf{c}_{-i}, \text{Rest}) \propto \begin{cases} \tilde{J}_c F(x_i \mid \{X_i\}_{i \in c} Y_c^*) & \text{if existing} \\ \frac{V}{M} F(x_i \mid Y_c^*) & \text{if new} \end{cases}$   
**if**  $c' \in [M]$  **then**  
     $\tilde{J}_{\text{new}} \leftarrow \text{ExactSampleNewTableSize}(V, \sigma \mid \text{rest})$   
     $V \leftarrow V - \tilde{J}_{\text{new}}$   $\triangleright$  Remove it from the old surplus  
     $\Pi_n \leftarrow \Pi_n \cup \{\{i\}\}$   
     $Y_{\{i\}}^* \leftarrow Y_{c'}^e$   
     $Y_{c'}^e \sim H_0$   
**else**  
     $c' \leftarrow c' \cup \{i\}$   
**end if**  
Draw  $\{Y_j^e\}_{j=1}^M \stackrel{\text{i.i.d.}}{\sim} H_0$

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**Algorithm 4** ExactSampleNewTableSize( $V, \sigma \mid \text{rest}$ )

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**if**  $\sigma = 0.5$  **then**  
     $G \sim \text{Gamma}(\frac{3}{4}, 1)$   
     $IG \sim \text{Inverse Gamma}(\frac{1}{4}, \frac{1}{4^3} V^{-2})$   
     $V_{\text{stick}} = \frac{\sqrt{G}}{\sqrt{G} + \sqrt{IG}}$   
     $\tilde{J}_{\text{new}} = V_{\text{stick}} V$   
**else**  
    **if**  $\sigma < 0.5$  &&  $\sigma = \frac{u_\sigma}{v_\sigma}, u_\sigma, v_\sigma \in \mathbb{N}$  **then**  
         $\lambda = u_\sigma^2 / v_\sigma^{\frac{v_\sigma}{u_\sigma}}$   
         $IG \sim \text{Inverse Gamma}(1 - \frac{u_\sigma}{v_\sigma}, \lambda)$   
         $\frac{1}{G} \sim \mathcal{E}_T(\lambda, L \frac{u_\sigma}{v_\sigma}^{-1/u})$   $\triangleright$  Samples an exponentially tilted random variable. See Favaro  
*et al.* [1] for details.  
         $V_{\text{stick}} = \frac{G}{G + IG}$   
         $\tilde{J}_{\text{new}} = V_{\text{stick}} V$   
    **end if**  
**end if**

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## 2 Relationship to the Pitman-Yor's Stick-breaking construction

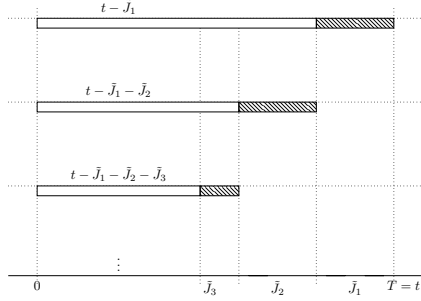


Figure 1: Generative process of Section 2.1

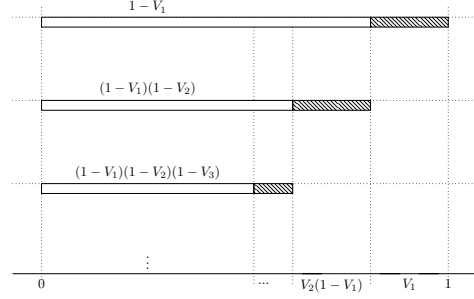


Figure 2: Pitman-Yor's stick breaking construction

$$\begin{aligned}
 T &\sim \gamma_{PY} \\
 \tilde{J}_1 &| T \sim \text{SBS}(T) \\
 \tilde{J}_2 &| T, \tilde{J}_1 \sim \text{SBS}\left(T - \tilde{J}_1\right) \\
 &\vdots \\
 \tilde{J}_\ell &| T, \tilde{J}_1, \dots, \tilde{J}_{\ell-1} \sim \text{SBS}\left(T - \sum_{i < \ell} \tilde{J}_i\right) \\
 &\vdots \\
 P_\ell &\stackrel{d}{=} \frac{\tilde{J}_\ell}{T - \sum_{j < \ell} \tilde{J}_j}
 \end{aligned}$$

$$\begin{aligned}
 V_1 &\sim \text{Beta}(v_1 | 1 - \sigma, \theta + \sigma) \\
 V_2 &\sim \text{Beta}(v_2 | 1 - \sigma, \theta + 2\sigma) \\
 &\vdots \\
 V_\ell &\sim \text{Beta}(v_\ell | 1 - \sigma, \theta + \ell\sigma) \\
 &\vdots
 \end{aligned}$$

the corresponding weights are:

$$P_\ell \stackrel{d}{=} V_\ell \prod_{j < \ell} (1 - V_j).$$

The Pitman Yor's stick breaking construction from Ishwaran & James [2] can be recovered from the size-biased sampling (SBS) generative process of Section 2.1 after integrating out the total mass  $T$ , the change of variables given in Section 2.2 and if we choose a specific distribution for the total mass

$$\gamma_{PY}(t) = \frac{\Gamma(\theta + 1)}{\Gamma(\frac{\theta}{\sigma} + 1)} t^{-\theta} f_\sigma(t) \mathbb{I}_{(0, \infty)}(t), \quad \theta > -\sigma$$

which corresponds to the Pitman-Yor prior and  $f_\sigma$  is the density of a  $\sigma$ -Stable random variable.

## References

- [1] Favaro, S., Lomeli, M., Nipoti, B., & Teh, Y. W. 2014. On the Stick-Breaking representation of  $\sigma$ -Stable Poisson-Kingman models. *Electronic Journal of Statistics*, **8**, 1063–1085.
- [2] Ishwaran, H., & James, L. F. 2001. Gibbs Sampling Methods for Stick-Breaking Priors. *Journal of the American Statistical Association*, **96**(453), 161–173.
- [3] Pitman, J. 1996. Random discrete distributions invariant under size-biased permutation. *Advances in Applied Probability*, **28**, 525–539.