

Appendix: A Layered Dirichlet Process for Hierarchical Segmentation of Sequential Grouped Data

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1 Block Exchangeability

In this section, we provide proofs of the three theorems on Block Exchangeability which are stated without proofs in the paper.

Theorem 1 *If a model defining a joint distribution P is Completely Exchangeable then it is necessarily Block Exchangeable, but not the converse.*

Proof. Consider any assignment \bar{z} of sequence z . Every time a particular value i is taken, the next value is either i or something other than i or it is the last entry, and so $n_i = n_{i,i} + n_{i,-i} + \delta(i, e)$, where n_i is the number of times the i -th value occurred in the sequence. So, the Exchangeability Statistic $S_C(z) = \{n_i\}$ can be uniquely determined from $S_B(z) = (\{n_{i,i}, n_{i,-i}\}, e)$.

Consider two assignments \bar{z}_1 and \bar{z}_2 of sequence z . From the above we know that $S_B(z_1) = S_B(z_2)$ implies $S_C(z_1) = S_C(z_2)$. But, since P is Completely Exchangeable by assumption, $S_C(z_1) = S_C(z_2)$ implies $P(z_1) = P(z_2)$. Combining, $S_B(z_1) = S_B(z_2)$ implies $P(z_1) = P(z_2)$. Hence, if a model is Completely Exchangeable then it is necessarily Block Exchangeable. But the entries in $S_B(z)$ cannot be obtained from $S_C(z)$ because any entry n_i cannot be uniquely split in to $n_{i,i}$ and $n_{i,-i}$. So, even though $S_C(z_1) = S_C(z_2)$, $S_B(z_1)$ need not be equal to $S_B(z_2)$. Hence, if a model is BE then it need not be CE.

Theorem 2 *If a model defining a joint distribution P is Block Exchangeable then it is necessarily Markov Exchangeable, but not the converse.*

Proof. Consider any assignment \bar{z} of sequence z . The Exchangeability Statistic $S_B(z) = (\{n_{i,i}, n_{i,-i}\}, e)$ can be uniquely determined from $S_M(z) = (\{n_{ij}\}, s)$, since $n_{i,i} = n_{ii}$ and $n_{i,-i} = \sum_{j \neq i} n_{ij}$.

Consider two assignments x and y of sequence X . From the above we know that $S_M(x) = S_M(y)$ implies $S_B(x) = S_B(y)$. But, since P is Block Exchangeable by assumption, $S_B(x) = S_B(y)$ implies $P(x) = P(y)$. Combining, $S_M(x) = S_M(y)$ implies $P(x) = P(y)$. Hence, if a model is Block Exchangeable then it is necessarily Markov Exchangeable. But the entries in $S_M(z)$ cannot be obtained

from $S_B(z)$ because any entry $n_{i,-i}$ cannot be uniquely split in to $n_{i,j}$, for all $j \neq i$. So, even though $S_B(x) = S_B(y)$, $S_M(x)$ need not be equal to $S_M(y)$. Hence, if a model is ME then it need not be BE.

Theorem 3 *The BE-DP prior distribution as well as the corresponding mixture model satisfy Block Exchangeability.*

Proof. Consider the generative process in Eqn. 6. Given π and q , the joint probability of a sequence $\{z_i, g_i\}$ without the observations w_i can be factorized as

$$p(z_{j_1}, z_{j_2}, \dots, z_{j_n} | \pi, q) = p(z_{j_1} | \pi) \prod_{i=2}^n p(z_{j_i} | z_{j_{i-1}}, \pi, q)$$

where $\{j_1, j_2, \dots, j_n\} = \{i : g_i = g\}$, for some unique value g . Now clearly, $p(z_{j_1}) = \prod_{k=1}^K \pi^{\delta(k, z_{j_1})}$ and

$$p(z_{j_i} | z_{j_{i-1}}) = \prod_{k=1}^K (\hat{\pi}_{gk}(k))^{\delta(k, z_{j_{i-1}}) \delta(z_{j_i}, z_{j_{i-1}})} q_{gk}^{\delta(k, z_{j_{i-1}}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))} \times \prod_{k'=1}^K \pi_g(k')^{\delta(k', z_{j_i}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))}$$

Taking the product over i , we finally get the full probability as

$$p(z_{j_1}, \dots, z_{j_n}) = \prod_{k=1}^K (\hat{\pi}_{gk}(k))^{\sum_{i=2}^n \delta(k, z_{j_{i-1}}) \delta(z_{j_i}, z_{j_{i-1}})} \times \prod_{k=1}^K q_{gk}^{\sum_{i=2}^n \delta(k, z_{j_{i-1}}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))} \times \prod_{k=1}^K \pi_g(k)^{\delta(k, z_{j_1}) + \sum_{i=2}^n \delta(k, z_{j_i}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))}$$

The first term corresponds to the case that $z_{j_i} = z_{j_{i-1}}$, and the next two terms are for the case where they are not equal.

Now, the term $\sum_{i=2}^n \delta(k, z_{j_{i-1}}) \delta(z_{j_i}, z_{j_{i-1}})$ equals the number of times the value k has been retained from the previous step, i.e. the number of self transitions from value k , which is denoted $n_{k,k}$.

Next, the term $\sum_{i=2}^n \delta(k, z_{j_{i-1}}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))$ is the number of transitions made from value k to some other value, which is denoted by $n_{k,-k}$.

Finally, the term $\delta(k, z_{j_1}) + \sum_{i=2}^n \delta(k, z_{j_i}) (1 - \delta(z_{j_i}, z_{j_{i-1}}))$ is the number of transitions made to k from some other value or the start. But a transition made to value k has a corresponding transition out of value k , unless k is the end-value e . If $k = e$, the above term is $n_{k,-k} + 1$. In other words, the above term is $n_{k,-k} + \delta(k, e)$.

So the probability of the given sequence is

$$p(z_{j_1}, \dots, z_{j_n}) = \prod_{k=1}^K (\hat{\pi}_{gk}(k))^{n_{k,k}} q_{gk}^{n_{k,-k}} \pi_g(k)^{n_{k,-k} + \delta(k, e)}$$

Clearly, the probability of a sequence depends only on $(\{n_{k,k}, n_{k,-k}\}_k, e)$, which proves the model is Block-Exchangeable.

2 Mixed Exchangeability Model

In the paper we have defined generative processes satisfying CE,ME and BE for any particular layer. A particularly attractive property of the LaDP framework is that, it allows the use of any exchangeability property for any layer. To illustrate the generative process of such a mixed-exchangeability LaDP model, we describe in detail the generative process for a model with $L = 2$, where we have ME at $l = 2$ and BE at $l = 1$. We also have layer $l = 0$ to generate the observations, which uses CE. According to the nomenclature of Section 6 in the paper, this is called ME-BE-CE-LaDP.

$$\begin{aligned}
\beta_{g_2}^2 &\sim GEM(\gamma^2); \pi_{g_2, g_2'}^2 \sim DP(\alpha^2, \beta_{g_2}^2), g_2, g_2' = 1 \dots \infty \\
\beta_{g_1}^1 &\sim GEM(\gamma^1); \pi_{g_1}^1 \sim DP(\alpha^1, \beta_{g_1}^1), g_1 = 1 \dots \infty \\
q_{g_1, g_1'}^1 &\sim Beta(1, \kappa); \pi_{g_1, g_1'}^1 = q_{g_1, g_1'}^1 \pi_{g_1}^1 + (1 - q_{g_1, g_1'}^1) \delta_{g_1'}, g_1, g_1' = 1 \dots \infty \\
\beta_{g_0}^0 &\sim GEM(\gamma^0); \pi_{g_0}^0 \sim DP(\alpha^0, \beta_{g_0}^0); g_0 = 1 \dots \infty
\end{aligned}$$

$$\begin{aligned}
z_i^2 &\sim \pi_{z_i^3, p(i,2)}^2, i = 1 \dots n \\
z_i^1 &\sim \pi_{z_i^2, p(i,1)}^1, i = 1 \dots n \\
z_i^0 &\sim \pi_{z_i^1}^0; w_i = \mathcal{W}_{z_i^0}, i = 1 \dots n
\end{aligned}$$

For the first datapoint of each group at layer $(l + 1)$, where $p(i, l)$ is undefined, we sample $z_i^l \sim \beta_{z_i^{l+1}}^l$, for $l = \{2, 1\}$.

z_i^3 and w_i are observed for all $i \in [1, n]$.