How Chinese Restaurants Can Help with Robust Preference Insights: A Novel Dirichlet Mixture Model to Account for Complex Heterogeneity in Individual Preference Weights

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Background

- Individual-level preference-elicitation methods, such as thresholding or swing-weighting, have been proposed in the literature to facilitate the collection of stakeholder preferences in small samples. For instance, understanding the benefit-risk trade-offs that individuals with a rare disease are willing to make can support the regulatory evaluation of novel therapies or help determine patient-relevant changes in de novo endpoints.[1,2]
- While such individual-level data provide rich insights into preference heterogeneity by design, sample-level characterizations can be challenging. Given that many decisions happen at the population level, this challenge is of practical relevance.
- Dirichlet regression has been suggested for averaging individual-level preference data in this context. However, Dirichlet distributions impose restrictive assumptions. Specifically, the Dirichlet distribution is unimodal, symmetric, and imposes a rigid, always negative correlation structure between parameters (*see* **Box 1**).[3-5]
- These restrictions do not hold if preferences cluster across different treatment priorities. For instance, some patients may focus on maximizing treatment efficacy, while others minimize treatment risks.
- Accounting for complex heterogeneity patterns in preference research is important for decision making along the entire healthcare life cycle and avoids biased preference estimates.[6]

Objectives

- **To quantify the bias in mean estimates from standard Dirichlet regression in the presence of multimodal preferences.**
- **To explore the application of a continuous Dirichlet mixture (CDM) model that combines multiple Dirichlet distributions using a Chinese restaurant process (CRP), to account for multimodal preferences.**

Box 1. Dirichlet Distribution: Overview

Setup

Assume $\omega = \{\omega_1; \omega_2; \ldots; \omega_K\}$ are preference weights of K attributes that are distributed on the $K-1$ simplex, such that $\omega_k \in \Omega = \left\{\omega_k \in \mathbb{R}^K; \omega_k > 0; \sum_{k\in[1;K]} \omega_k = 1\right\}$. Here ω follows a Dirichlet distribution with the parameters $\alpha = \{\alpha_1; \alpha_2; \ldots; \alpha_K\}$.

Density

$$f_\omega = \frac{\Gamma\left(\sum_{k\in[1;K]} \alpha_k\right)}{\prod_{k\in[1;K]} \Gamma(\alpha_k)} \prod_{k\in[1;K]} \omega_k^{\alpha_k - 1} \text{ with } \alpha_k > 0$$

Structure

- Symmetric and unimodal distribution over Ω.
- Fixed correlation of $\rho_{kj} = -\sqrt{\alpha_k \alpha_j / [(\alpha_0 - \alpha_k)(\alpha_0 - \alpha_j)]}$

Bias Evaluation

- We used a simulation approach to quantify the bias in estimated mean preference weights (see **Box 1**) from a standard (i.e., unimodal) Dirichlet regression in a five-attribute decision problem, assuming in the presence of multimodal preference heterogeneity.
  - For example, assuming everyone prefers to minimize risk, when there may be a cluster of individuals who want to minimize risk while another cluster of individuals wants to maximize benefits.
- Simulated Dirichlet distributions (**Table 1**) were specified to either have a large or a small overlap, which was quantified using the Bhattacharyya distance (BD). Up to three distributions were probabilistically mixed with equal weights for both overlap scenarios assuming a small (*N*=60) and large sample size (*N*=150).
- Bias was calculated as the percentage difference between estimated and true mean preference weights.
- Results are displayed in the left column of **Figure 1**. The average bias ranged from 1.5%–12.8% across the five attributes. As expected, the bias was small (≤5%) in the case of unimodal preferences. In case of large overlaps, multimodal Dirichlet distributions collapse, and the standard model (one Dirichlet distribution) fitted the joint distribution with small bias (≤5%).
- However, as distributions (preference clusters) became more distinct, average bias increased to >15% for some estimates.

Table 1. Simulated Dirichlet Distributions

	True concentration parameters $(\alpha_1; \alpha_2; \alpha_3; \alpha_4; \alpha_5)$		
Overlap	$f_{\omega\|1}$	$f_{\omega\|2}$	$f_{\omega\|3}$
Small (BD: 11.1% – 20.8%) [a]	(1.0; 2.0; 3.0; 4.0; 5.0)[b]	(5.0; 4.0; 3.0; 2.0; 1.0)	(8.0; 2.0; 10.0; 4.0; 6.0)
Large (BD: 73.7% – 83.9%) [a]		(2.0; 3.0; 3.0; 3.0; 4.0)	(2.0; 1.5; 3.0; 5.0; 4.5)
	Simulated distributions		
Mixture	**N=50**		**N=150**
Unimodal	$f_{\omega\|1}$		$f_{\omega\|1}$
Two distribution mixture [c]	$1/2 * (f_{\omega\|1} + f_{\omega\|2})$		$1/2 * (f_{\omega\|1} + f_{\omega\|2})$
Three distribution mixture [c]	$1/3 * (f_{\omega\|1} + f_{\omega\|2} + f_{\omega\|3})$		$1/3 * (f_{\omega\|1} + f_{\omega\|2} + f_{\omega\|3})$

[a] min-max BD across binary comparison; [b] common concentration parameters across small and large overlap; [c] simulated once with small and once with large overlap (10 simulations in total)
Abbreviation: BD=Bhattacharyya distance

Continuous Dirichlet Mixture Model

- We proposed the use of a CDM model to account for multimodality in individual preference weights (*see* Setup in **Box 1**).
- Specifically, the model assumes that there are C priorities around which the preference weights cluster following different Dirichlet distributions. The number of priorities is unknown a priori and endogenously estimated via the model.

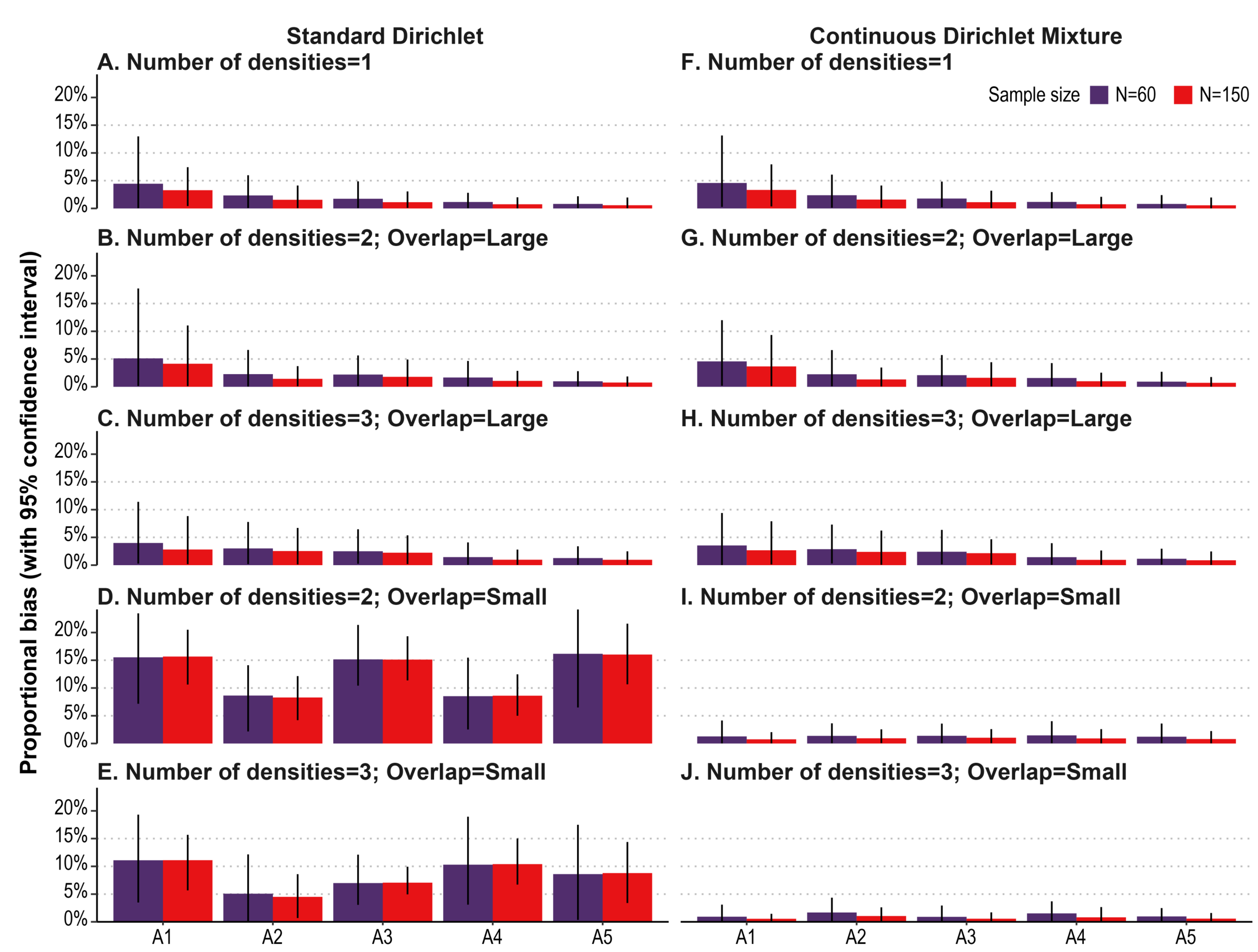
- The CRP assigns an individual to either:
  - a *new Dirichlet distribution* (preference cluster) that is generated proportionally to a concentration parameter δ, with the probability $\pi_n^{new} = \delta/(\delta + N + 1)$
  - or assigns the individual to *an already generated Dirichlet distribution* (preference clusters, *c)* with a probability proportional to the share of people previously assigned to that distribution (n_c out of the N total individuals), specifically $\pi_n^c = n_c/(\delta + N + 1) \, / \, ((\delta + N + 1))$
- The key property of this approach is that δ does not pre-specify the number of preference clusters, unlike in a latent class model, where this would be specified, but governs the discovery of the number of clusters, which grows at the rate $\delta \ln(N)$.

- The log-likelihood function of the model is given by $\mathcal{LL} = \sum_{n\in[1;N]} ln\left(\sum_{c\in[1;C_n-1]} \pi_n^c f_{\omega|c} + \pi_n^{new} f_{\omega|C_n}\right)$ with $f_{\omega|c}$ being the Dirichlet distribution of a given preference cluster (*see* **Box 1**) that is associated with cluster-specific preference weights $\omega^c = \{\omega_1^c;\ \omega_2^c; \ldots; \omega_K^c\}$.
- A Markov-Chain Monte Carlo approach was used for model estimation.

Model Performance

- The CDM model was evaluated using the same simulation that evaluated the standard Dirichlet regression (one distribution), and the results are displayed in the right column of **Figure 1**.
- For all cases, the CDM model performance was non-inferior or superior to the standard Dirichlet regression, with no differences in the case of unimodal preferences and negligible differences if the Dirichlet distributions had a large overlap (i.e., if the preference clusters had similarities in preference priorities).
- The average bias ranged from 0.9% to 2.3% across the five attributes.
  - In the case of multimodal preferences with small overlap between distributions (preference clusters), the estimation bias was reduced considerably to <5% with the CDM compared to standard Dirichlet regression (assuming only one cluster).
- The average estimation time was longer for the CDM (several minutes) compared to the standard Dirichlet regression (several seconds), but the difference is unlikely to be of practical relevance.

Figure 1. Percent Bias by Model



Conclusions and Recommendations

- **Not accounting for multimodality can bias mean preference weight estimates, but the magnitude of bias depends on the clustering of preference weights.**
  - In the case of a large overlap in preference priorities between clusters, the standard Dirichlet model performs well.
  - In the case of small overlap in preference priorities between clusters (i.e. distinct treatment priorities by cluster) the CDM model is preferrable.
- **We encourage researchers to explore complex patterns of heterogeneity in the analysis of preference data. Appropriate accounting for heterogeneity may reduce bias, and insights obtained from inspecting the joint distribution can be decision-relevant.**

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