Combining Gibbs Sampling with Hamiltonian Monte Carlo for Bayesian Diagnostic Model Estimation

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Diagnostic Classification Models

- Diagnostic models are psychometric models that classify respondents into latent classes based on their responses to a set of indicator variables (items)

- Hamiltonian Monte Carlo (HMC) sampling has shown great potential for estimating DMs; however, HMC cannot directly sample discrete variables (i.e., attributes)

- We propose a synthesis of **Gibbs sampling** and **Hamiltonian Monte Carlo** for estimation Bayesian diagnostic classification models (B-DCMs)

Overview of Research

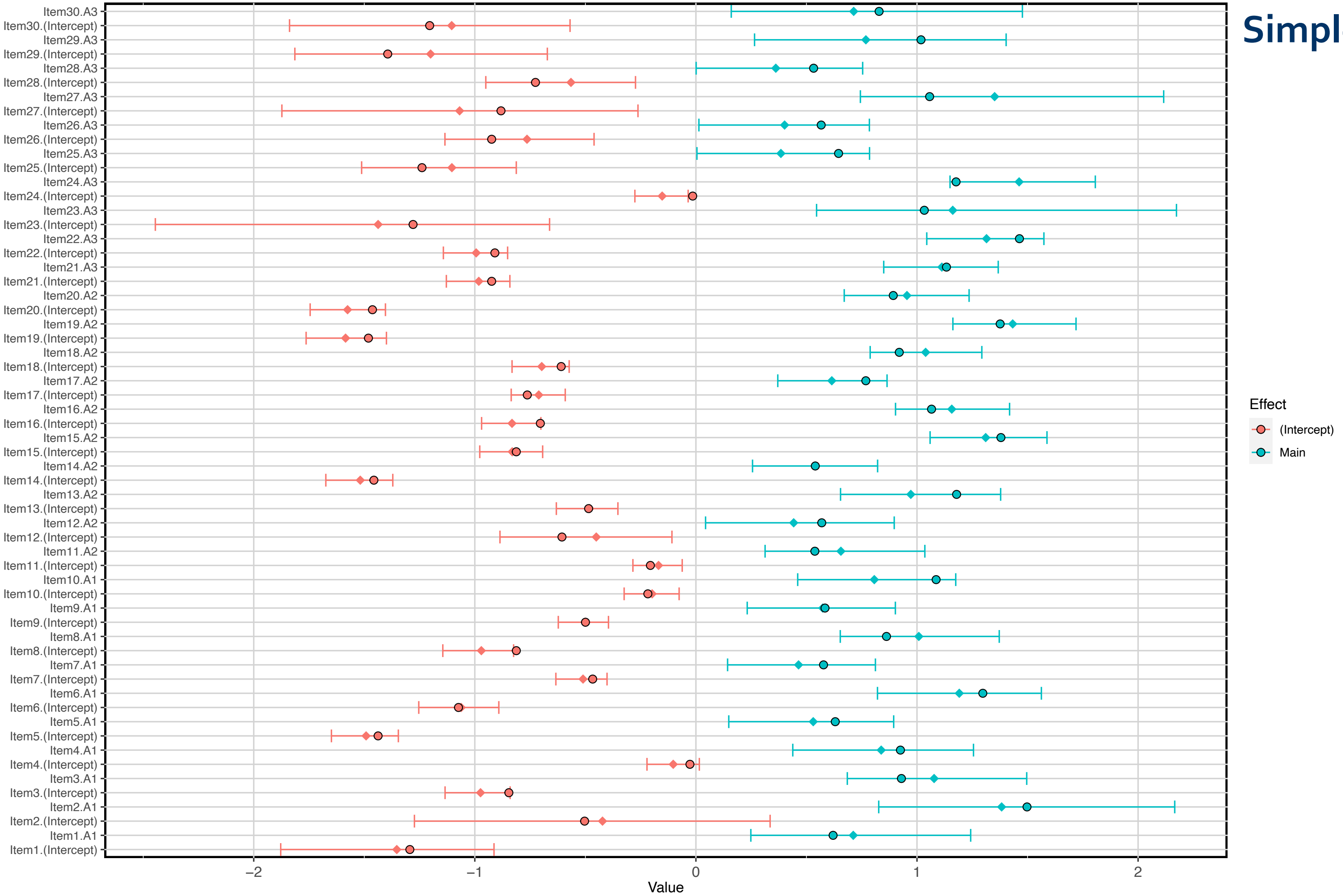
- Gibbs update: update **latent classes** and **latent class proportions** from **analytic posteriors**

- Hamiltonian update: update **item parameters** via evolution of **Hamiltonian dynamics**
  - Rejection sampling substep to avoid label switching
  - Random tuning hyperparameters to improve efficiency

- Preliminary simulation study:
  - Number of Items = 30, Sample size = 2,500, number of attributes = 3
  - Balanced Q-matrix (simple structure, complex structure)
  - Vary tuning hyperparameters (fixed or random)

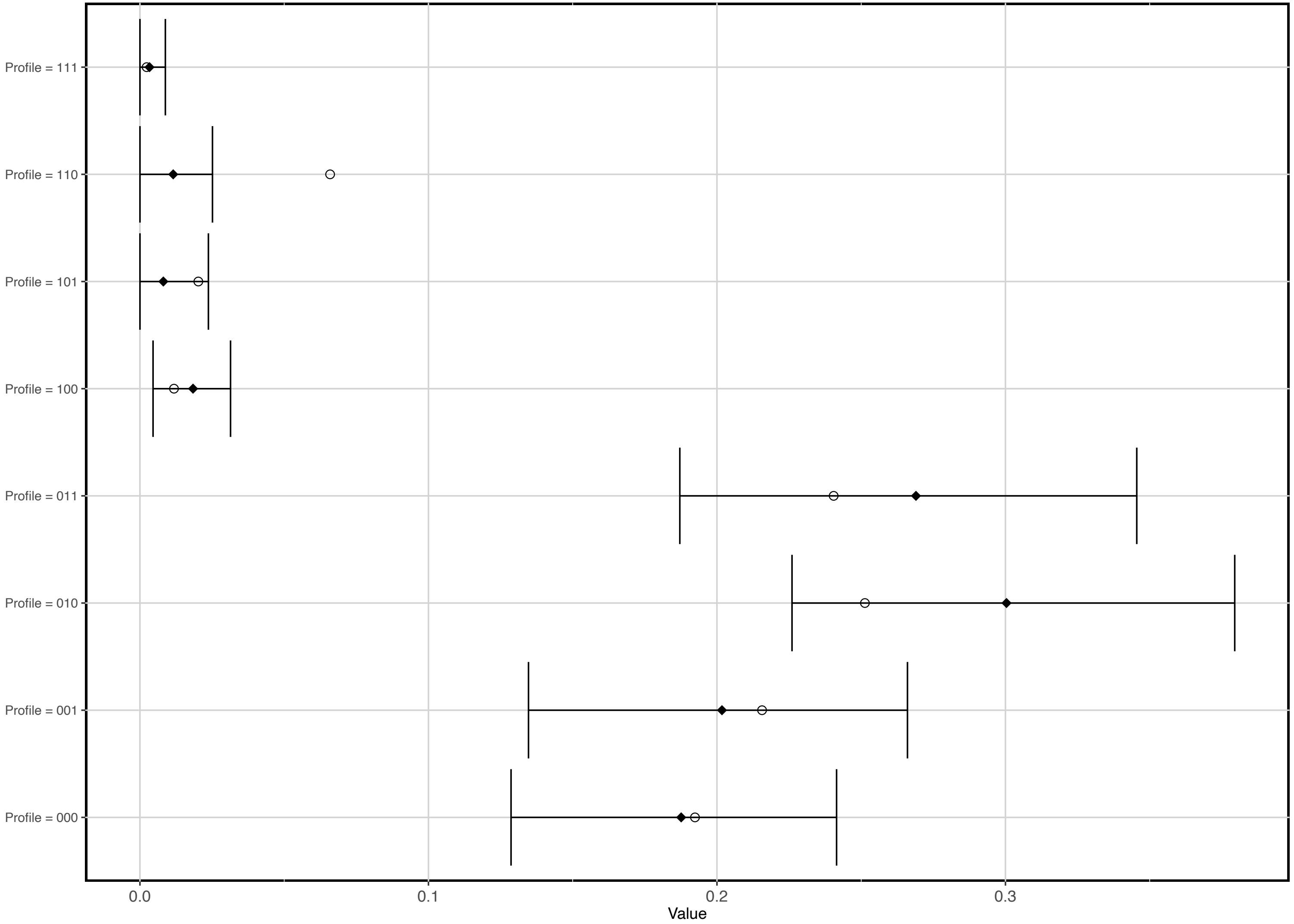
- Empirical Application: 95% credible intervals (comparison with stan)

Item Parameter Posterior Summaries



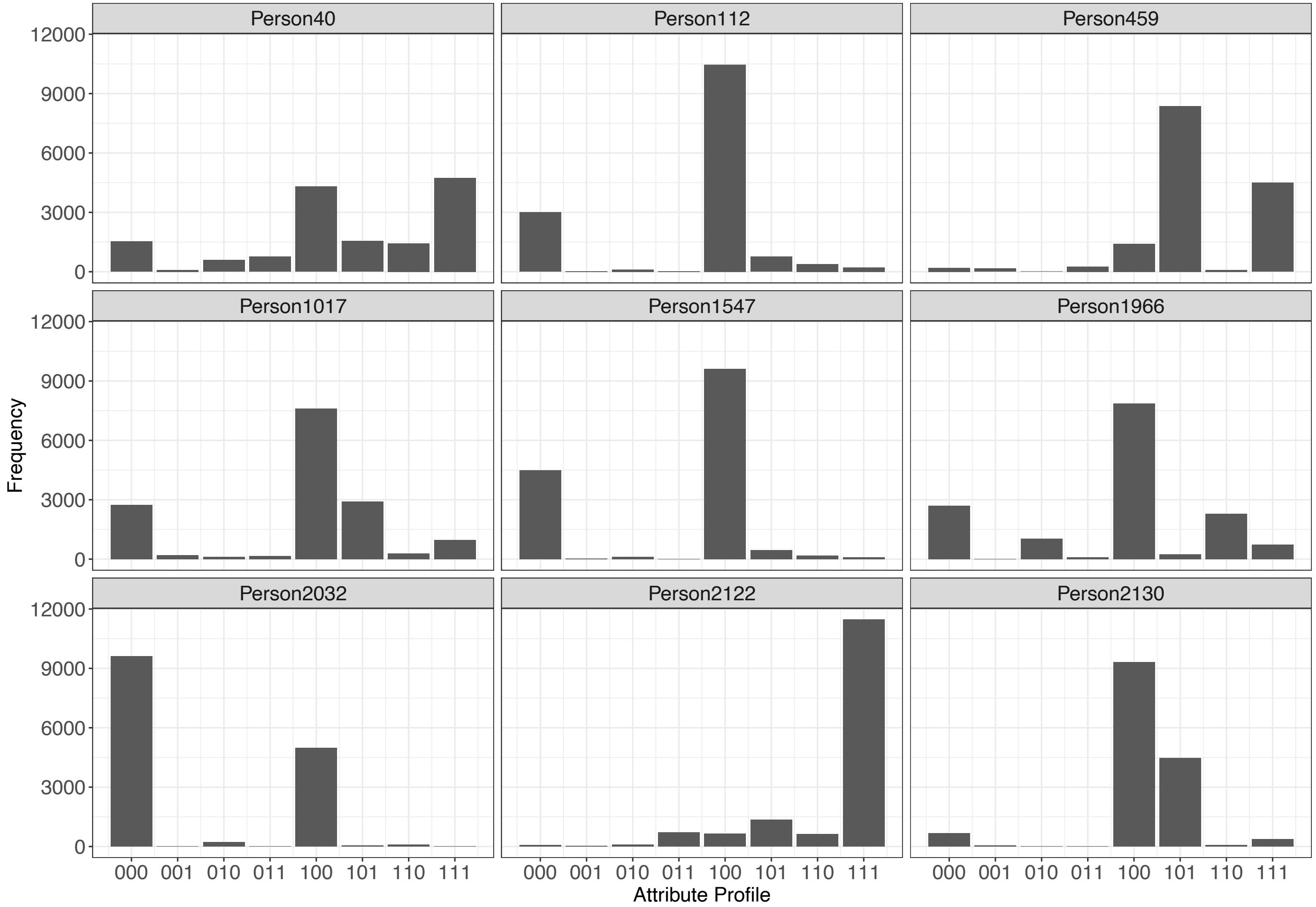
Simple Structure Model

Posterior Class Probabilities



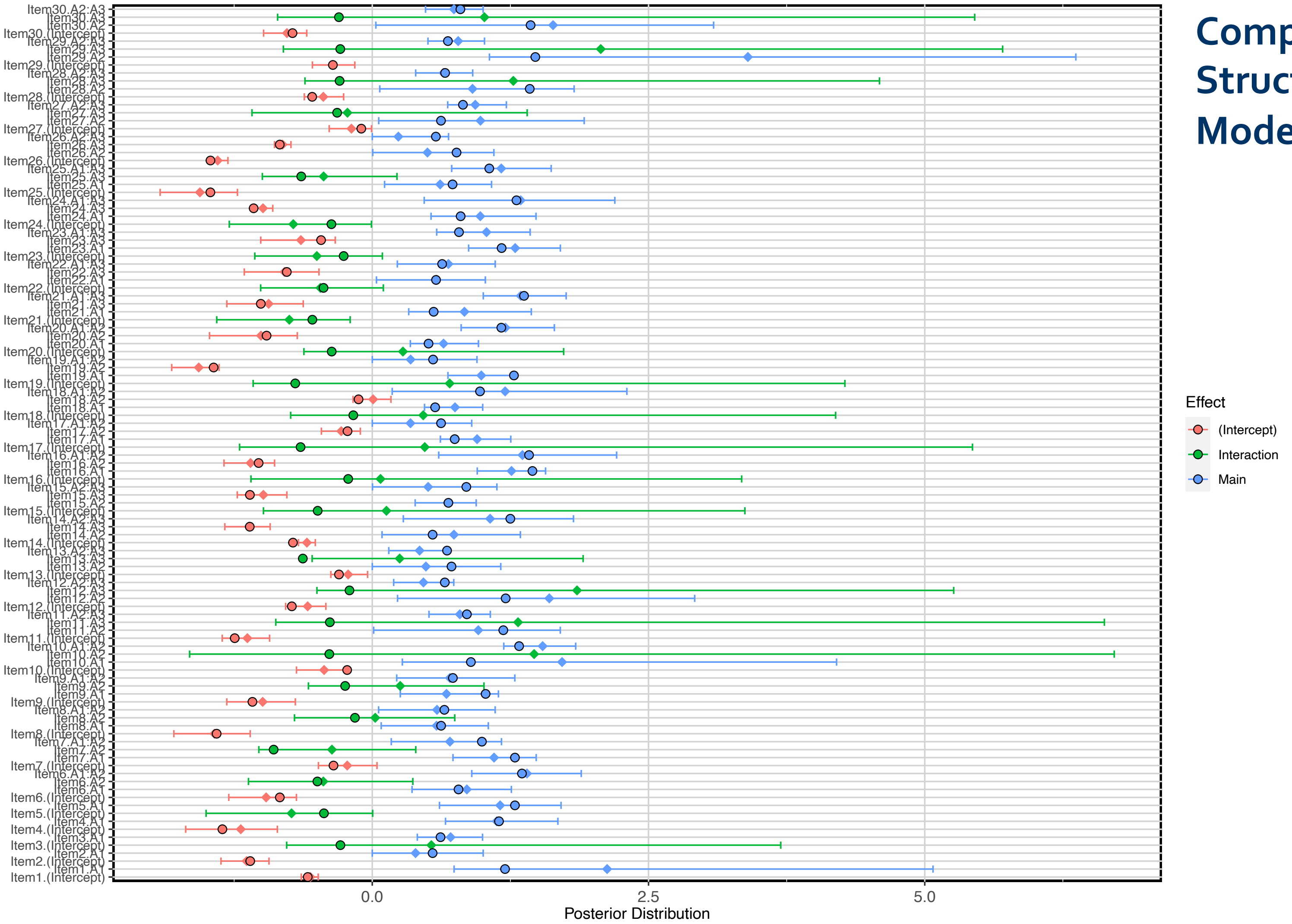
Simple Structure Model

Latent Class Posterior Distributions



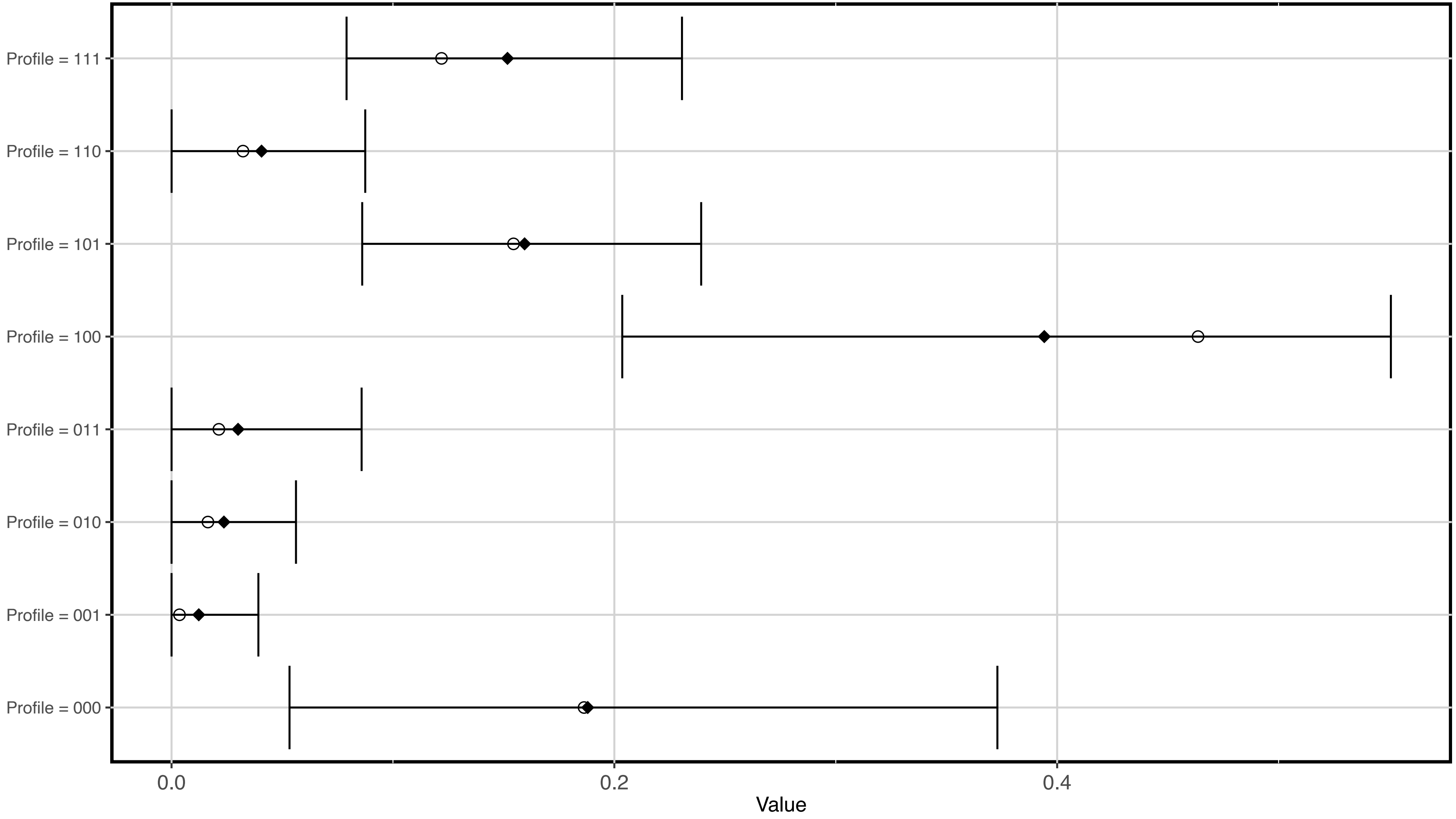
Latent class Posterior distributions for nine randomly selected respondents

Item Parameter Posterior Summaries



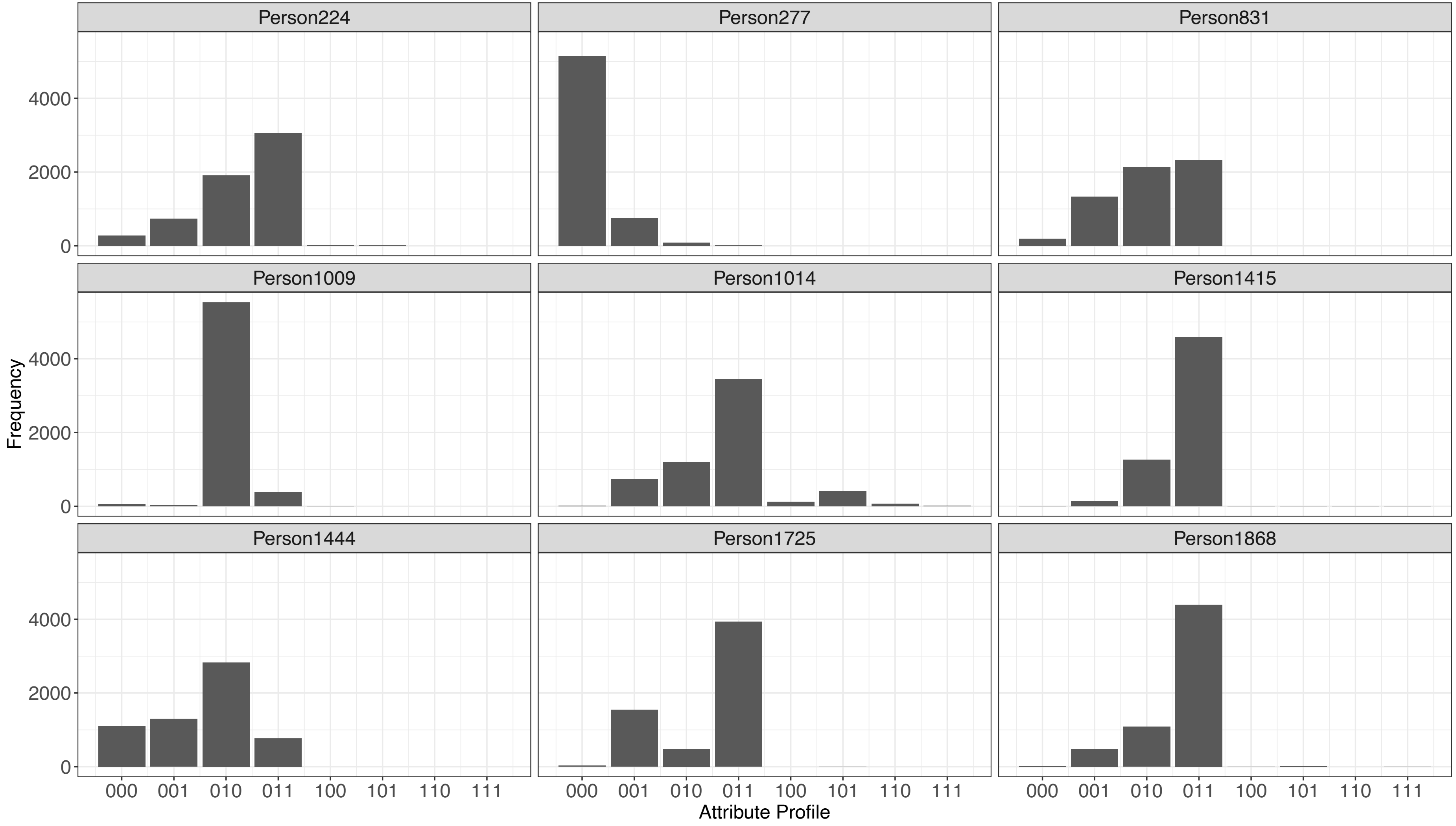
Complex Structure Model

Posterior Class Probabilities



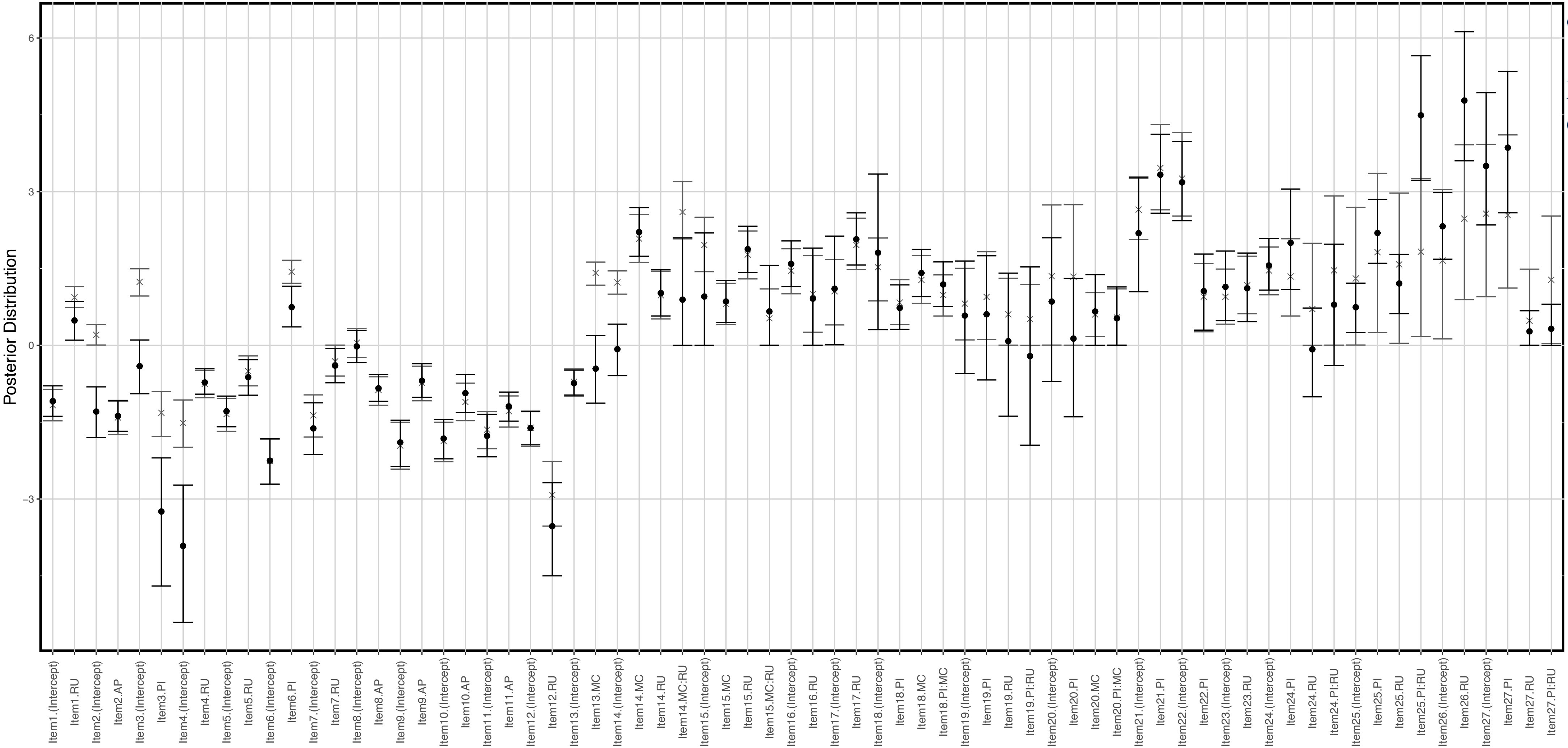
Complex Structure Model

Latent Class Posterior Distributions



Latent class Posterior distributions for nine randomly selected respondents

Empirical Application: DTMR



Grey bars: GibbsHMC

Black bars: NUTS (stan)

Takeaways

- Preliminary results suggest **good parameter recovery**
  - Latent interactions were sampled less efficiently than intercept and main effect parameters
- Random tuning parameters were found to lead to more efficient sampling than fixed tuning parameters
- Limitation: no direct comparison with existing samplers (yet; future direction)
- Future direction: Modify algorithm so that latent interactions are sampled more efficiently