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Conjugate prior in the Mallows model with Spearman distance

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Introduction

► **Ranking and comparing items:** crucial for collecting information about preferences in many areas: e.g. marketing, business, politics, genetics.

► **Mallows model:** powerful model for rankings

► **Question:** How to include **expert opinions** into the analysis? How to elicit a meaningful **prior on the consensus** ranking of a population?

1. The Mallows model with Spearman distance

The **Mallows model** (Mallows 1957) is a class of non-uniform distributions for $\mathbf{R} \in \mathcal{P}_n$, the set of n -dimensional permutations, of the form

$$P(\mathbf{R}|\theta, \boldsymbol{\rho}) = \frac{e^{-\theta d(\mathbf{R}, \boldsymbol{\rho})}}{Z(\theta)}$$

► $\boldsymbol{\rho} \in \mathcal{P}_n$: consensus ranking, location parameter

► $\theta \geq 0$: precision parameter

► $d(\cdot, \cdot)$: right-invariant (Diaconis 1988) distance

► $Z(\theta) = \sum_{\mathbf{r} \in \mathcal{P}_n} e^{-\theta d(\mathbf{r}, \mathbf{1}_n)}$: partition function (independent of $\boldsymbol{\rho}$ because of right-invariance of $d(\cdot, \cdot)$)

Spearman distance: the squared l_2 norm on \mathcal{P}_n

$$d_S(\boldsymbol{\rho}, \boldsymbol{\sigma}) = \sum_{i=1}^n (\rho_i - \sigma_i)^2, \quad \boldsymbol{\rho}, \boldsymbol{\sigma} \in \mathcal{P}_n$$

Consider n items, ranked by N assessors.

Denote by $\mathbf{R}_j = (R_{1j}, R_{2j}, \dots, R_{nj}) \in \mathcal{P}_n$, the ranking of user j , $j = 1, \dots, N$.

Under the Mallows model with Spearman distance (MMS), given θ , the likelihood can be written as

$$P(\mathbf{R}_1, \dots, \mathbf{R}_N | \boldsymbol{\rho}) \propto \exp\left(2\theta N \sum_{i=1}^n \rho_i \bar{R}_i\right)$$

where $\bar{R}_i = \frac{1}{N} \sum_{j=1}^N R_{ij}$, $i = 1, \dots, n$, is the sample average of the i -th rank.

2. Sufficient statistics and mle

The sufficient statistic for $\boldsymbol{\rho} = (\rho_1, \dots, \rho_n)$, when θ is known, is $\bar{\mathbf{R}} = (\bar{R}_1, \dots, \bar{R}_n)$.

Proposition 1. Let $\mathbf{R}_1, \dots, \mathbf{R}_N | \boldsymbol{\rho}, \theta \sim \text{Mall}(\theta, \boldsymbol{\rho})$, and define the vector of sample ranks $\bar{\mathbf{R}}$ as above. Assume $\bar{R}_i \neq \bar{R}_j$, for each $i \neq j$, and denote by $\mathbf{Y}(\bar{\mathbf{R}}) = [Y_1(\bar{\mathbf{R}}), \dots, Y_n(\bar{\mathbf{R}})] \in \mathcal{P}_n$ the rank vector of $\bar{\mathbf{R}}$, i.e. $Y_i(\bar{\mathbf{R}}) = Y_i = \sum_{h=1}^n \mathbb{1}(\bar{R}_h \leq \bar{R}_i)$, $i = 1, \dots, n$. Then the unique mle of $\boldsymbol{\rho}$ is

$$\boldsymbol{\rho}_{mle} = \operatorname{argmax}_{\boldsymbol{\rho} \in \mathcal{P}_n} \sum_{i=1}^n \rho_i \bar{R}_i = \mathbf{Y}(\bar{\mathbf{R}}).$$

Notice that, in general, $\bar{\mathbf{R}} \notin \mathcal{P}_n$. However $\bar{\mathbf{R}}$ lives in the permutohedron of order n .

Definition 1. The **permutohedron** of order n , $\mathbb{P}\mathcal{P}_n$, is an $(n-1)$ -dimensional polytope embedded in an n -dimensional space, the vertices of which are formed by permuting the coordinates of the vector $(1, 2, 3, \dots, n)$. Equivalently, it is the convex hull of the points $\boldsymbol{\rho} \in \mathcal{P}_n$, the set of n -dim permutations.

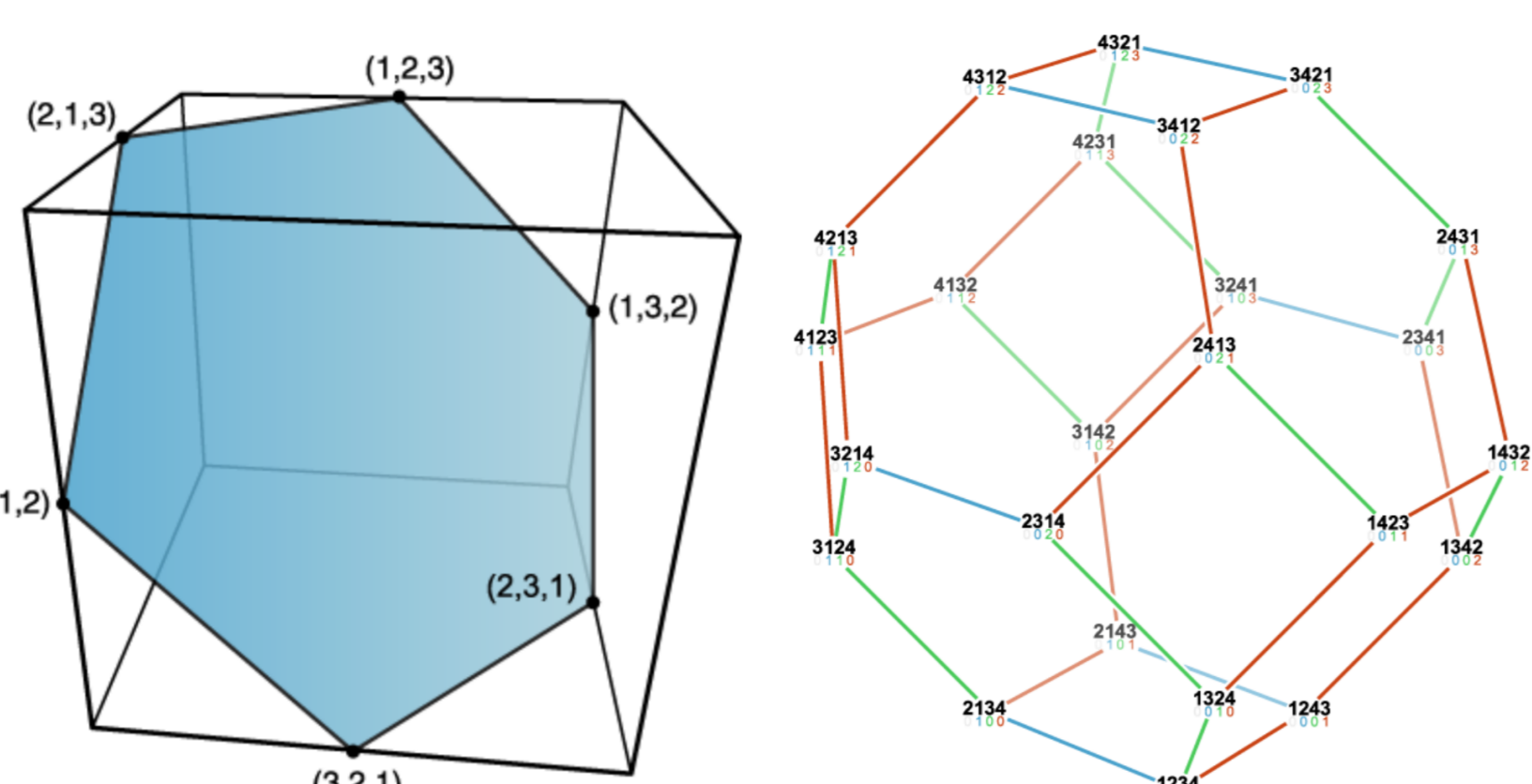


Figure 1: Left: The permutohedron of order 3 is a regular hexagon, filling a cross-section of a $2 \times 2 \times 2$ cube; Right: The permutohedron of order 4 is a truncated octahedron.

3. The Bayesian Mallows

Vitelli et al. (2018) proposed a framework for performing **Bayesian inference on the Mallows** model.

They assume that $\boldsymbol{\rho}$ is a priori uniformly distributed, $\boldsymbol{\rho} \sim \text{Unif}(\mathcal{P}_n)$.

Contribution: the objective prior in the sense of Villa & Walker (2015) is the uniform prior density on the space of permutations $\boldsymbol{\rho} \sim \text{Unif}(\mathcal{P}_n)$.

Can we go further?

How to put an informative prior on $\boldsymbol{\rho}$?

A: θ given: conjugate prior for $\boldsymbol{\rho}$

B: θ not given: conjugate conditioned on θ + clever prior on $\theta \rightarrow$ MH sampling scheme to approximate the posterior

3.A Conjugate prior for $\boldsymbol{\rho}$ (given θ)

Proposition 2. Keeping θ fixed, the conjugate prior for $\boldsymbol{\rho} \in \mathcal{P}_n$ is

$$\pi(\boldsymbol{\rho} | \boldsymbol{\rho}_0, \theta N_0) = \frac{\exp\left[-\theta N_0 \sum_{i=1}^n (\rho_i - \rho_{0i})^2\right]}{Z^*(\theta N_0, \boldsymbol{\rho}_0)},$$

where $\boldsymbol{\rho}_0 \in \mathbb{P}\mathcal{P}_n$, and $N_0 \in \mathbb{N}$. We call $\pi(\cdot | \boldsymbol{\rho}_0, \theta N_0)$ the extended Mallows density: it is a Mallows model where the consensus $\boldsymbol{\rho}_0$ belongs to $\mathbb{P}\mathcal{P}_n$.

Posterior consensus: weighted average of prior parameter and observed mean (recall Diaconis et al. 1979):

$$\boldsymbol{\rho}_N = \frac{N}{N_0 + N} \bar{\mathbf{R}} + \frac{N_0}{N_0 + N} \boldsymbol{\rho}_0 \in \mathbb{P}\mathcal{P}_n$$

$$\theta_N = \theta(N_0 + N) \in [0, \infty)$$

Then N_0 can be interpreted as an equivalent sample size (recall the Gaussian).

Remark 1. When $N_0 = 0$, the conjugate prior reduces to the uniform, for all $\boldsymbol{\rho}_0$. When $\boldsymbol{\rho}_0 = (\frac{n+1}{2}, \dots, \frac{n+1}{2})$ the conjugate prior reduces to the uniform, for all θ_0 .

3.A.bis Toy example 1

Sample $N = 30$ rankings from the MMS with $\boldsymbol{\rho} = (3, 1, 2)$ and $\theta = 0.18$. Conjugate prior with $\boldsymbol{\rho}_0 = (1, 2, 3)$, and varying $\theta_0 = \theta N_0$.

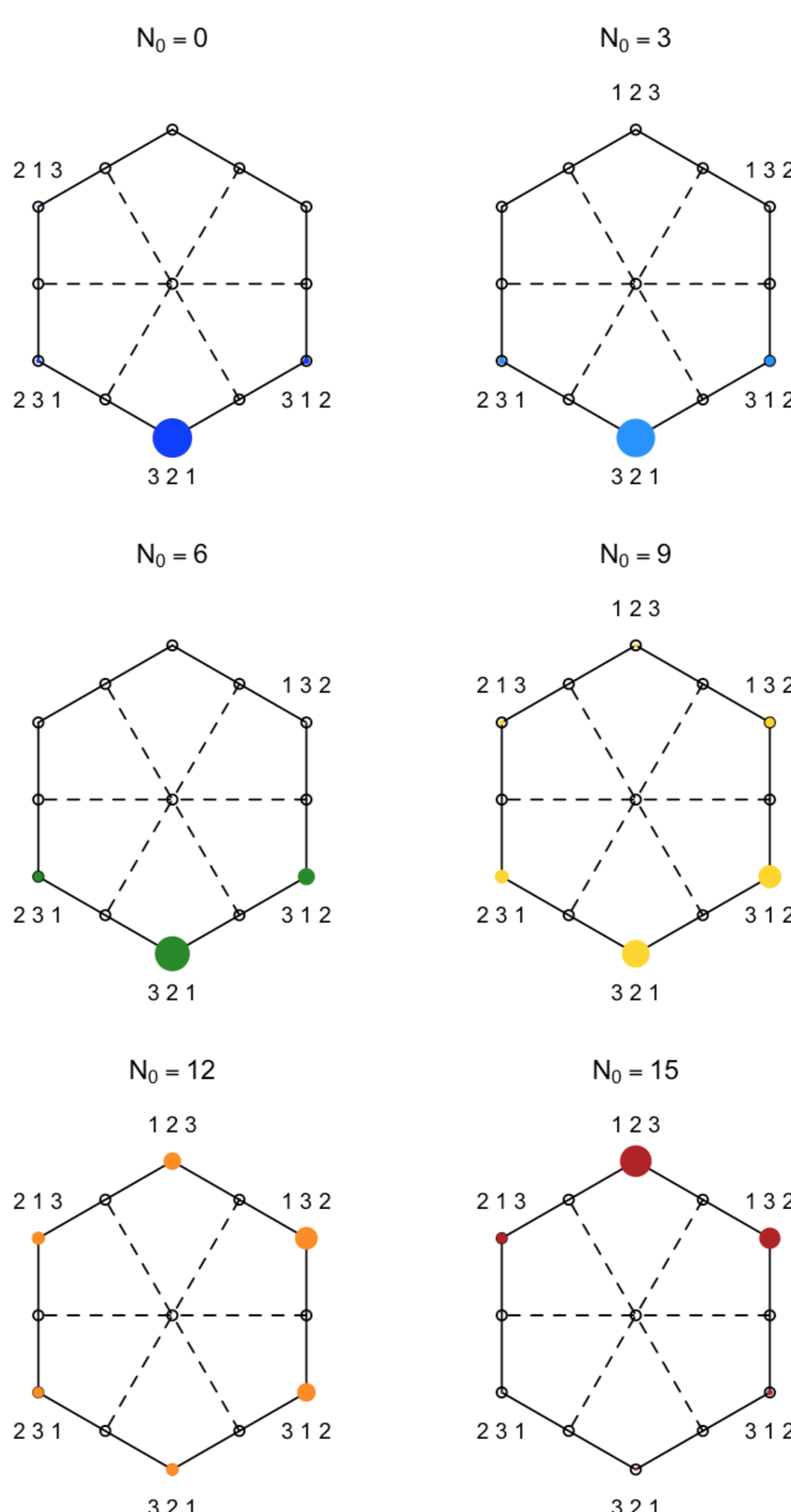


Figure 2: The balls have radius proportional to the frequency of rankings in the posterior sample.

3.A.bis Toy example 2

Same model. Increasing sample size (N). Conjugate prior with $\boldsymbol{\rho}_0 = (1, 2, 3)$ and $\theta N_0 = 3$ (i.e. $N_0 \approx 16$).

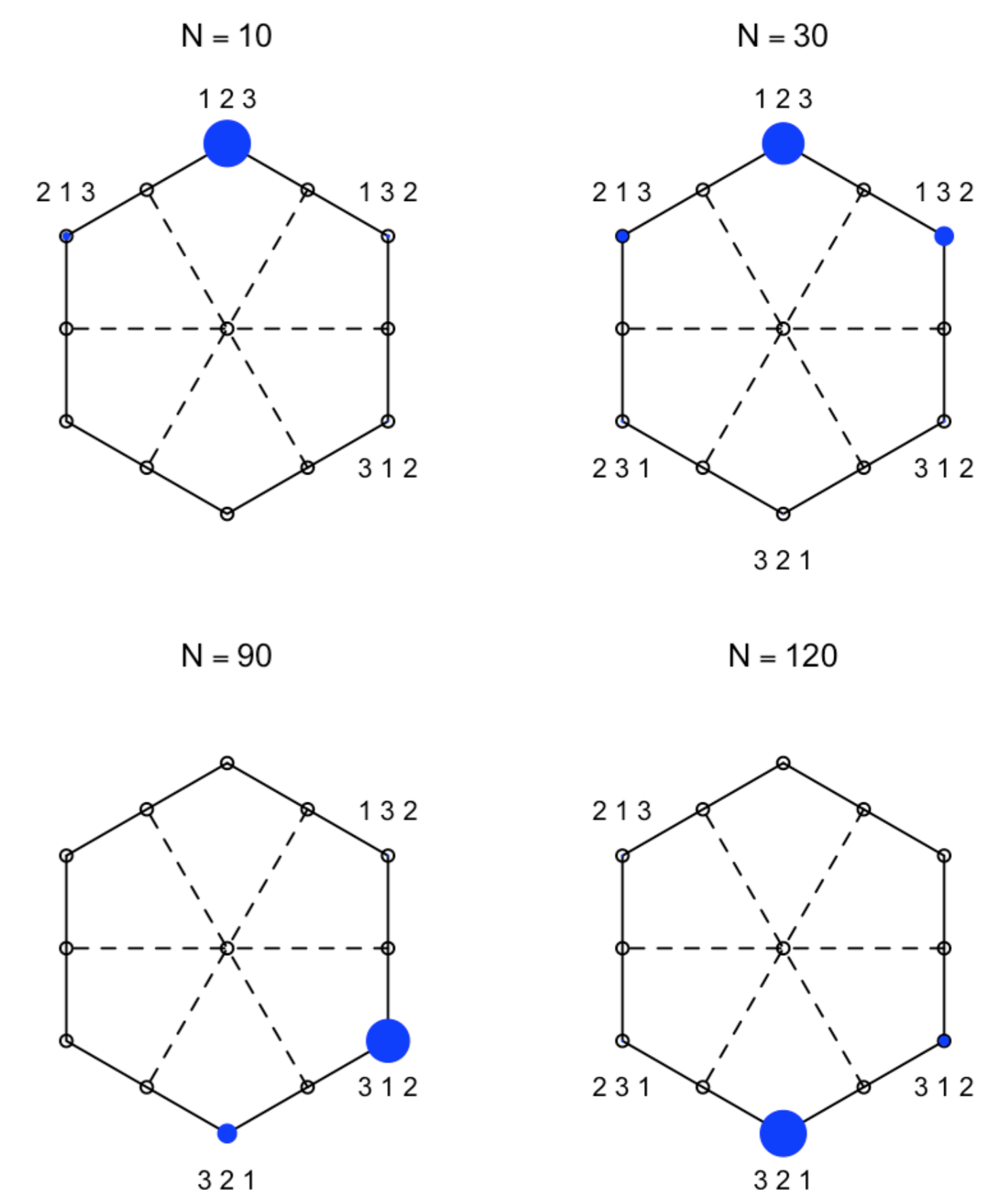


Figure 3: The balls have radius proportional to the frequency of rankings in the posterior sample.

3.B Prior when θ not given

When θ is unknown, the partition function of $\pi(\cdot | \boldsymbol{\rho}_0, \theta N_0)$ depends on the model parameters and cannot be avoided.

Solution: Let $\pi(\theta) \propto Z^*(\theta N_0, \boldsymbol{\rho}_0)$, so that the posterior full conditional is treatable.

3.B Prior when θ not given

Same model. Increasing sample size (N). $\boldsymbol{\rho}_0 = (1, 2, 3)$ and $N_0 = 16$.

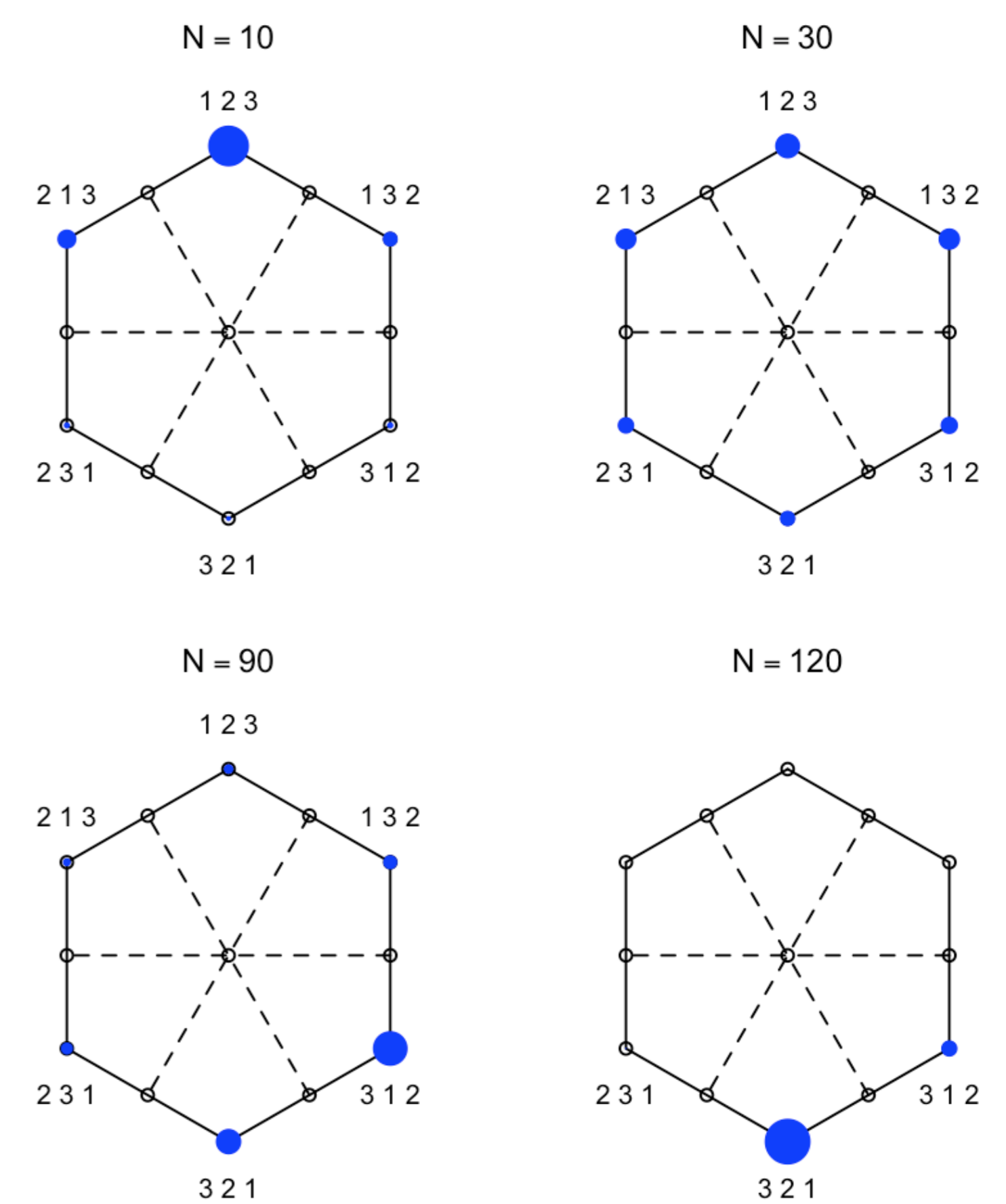


Figure 4: The balls have radius proportional to the frequency of rankings in the posterior sample.

Ongoing work

- Can we say something about the convergence rate? \rightarrow Can we say something about $Z^*(\cdot, \cdot)$?
- Applications?

Interesting data to test our methods on? Please take contact!

References

- Diaconis, P. (1988), *Group representations in probability and statistics*, Vol. 11 of *Lecture Notes - Monograph Series*, Institute of Mathematical Statistics, Hayward, CA, USA.
- Diaconis, P., Ylvisaker, D. et al. (1979), 'Conjugate priors for exponential families', *The Annals of statistics* **7**(2), 269–281.
- Mallows, C. L. (1957), 'Non-null ranking models. I', *Biometrika* **44**(1/2), 114–130.
- Villa, C. & Walker, S. (2015), 'An objective approach to prior mass functions for discrete parameter spaces', *Journal of the American Statistical Association* **110**(511), 1072–1082.
- Vitelli, V., Sørensen, Ø., Crispino, M., Frigessi, A. & Arjas, E. (2018), 'Probabilistic preference learning with the Mallows rank model', *Journal of Machine Learning Research* **18**(158), 1–49.