



Modeling Neural Population Coordination via a Block Correlation Matrix

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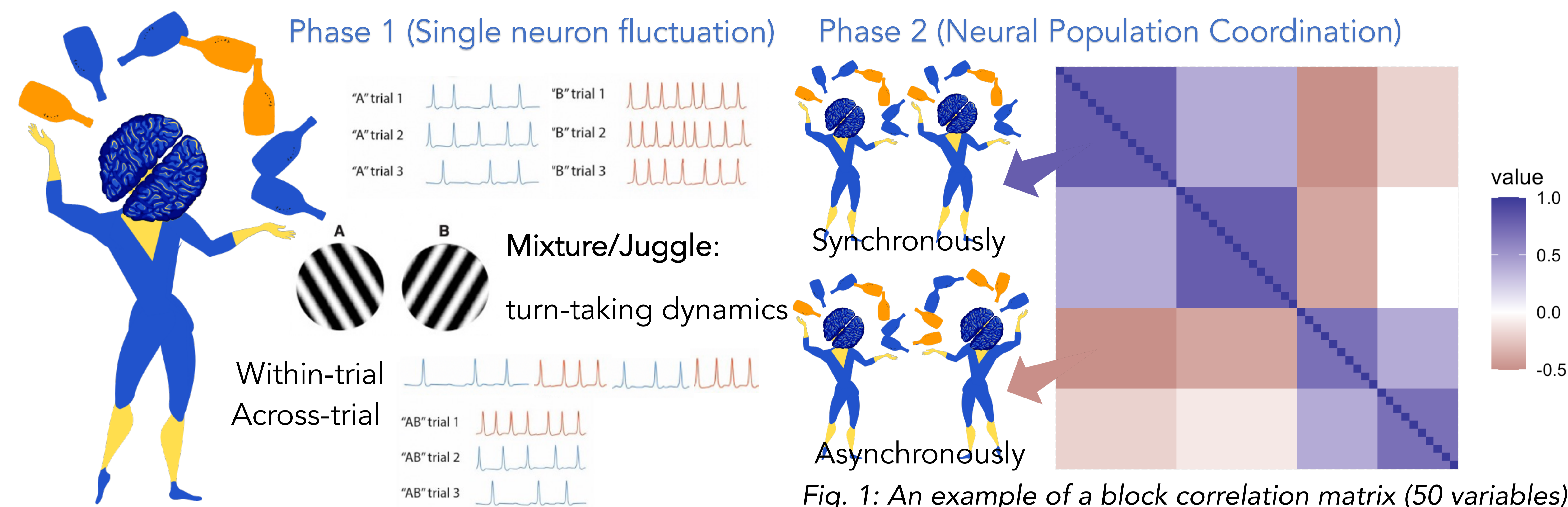


Fig. 1: An example of a block correlation matrix (50 variables)

Research Question

- Block correlation matrix estimation
- Unknown block structure: grouping w.r.t. variables
- Flexibility: off-diagonal correlation $\in (-1,1)$
- Interpretability: model assumptions + priors
- Statistical efficiency: large p small n cases
- Computational efficiency: conjugate priors

Method: Bayesian Block Correlation Matrix Estimation

- Permuted Data: $\tilde{Y} = PY, \tilde{Y} \sim N(0, \Sigma)$
- Canonical Representation of Block Covariance Matrix: (Archakov and Hansen, 2020)

$$\Sigma = \begin{bmatrix} \sigma_{11} & & & \\ & \sigma_{22} & & \\ & & \sigma_{33} & \\ & & & \ddots \end{bmatrix} = \begin{bmatrix} \nu_{n_1} & & & \\ & \nu_{n_2} & & \\ & & \nu_{n_3} & \\ & & & \ddots \end{bmatrix} \times \begin{bmatrix} \lambda_1 I_{n_1-1} & & & \\ & \lambda_2 I_{n_2-1} & & \\ & & \lambda_3 I_{n_3-1} & \\ & & & \ddots \end{bmatrix} \times \begin{bmatrix} & & & \\ & & & \\ & & & \\ & & & \ddots \end{bmatrix}$$

Block Covariance Orthonormal Pseudo-diagonal Orthonormal

- Correlation Matrix maintains SAME block structure if: $\sigma_i^2 \neq \sigma_{ii}$
- Interpretation: A Representatives $a_{ij} = \sigma_{ij} \sqrt{n_i n_j}$ $a_{ii} = \sigma_i^2 + (n_i - 1) \sigma_{ii}$
- λ Replicates $\lambda_i = \sigma_i^2 - \sigma_{ii}$
- Q Rotation $v_{n_k} = (\frac{1}{\sqrt{n_k}}, \dots, \frac{1}{\sqrt{n_k}})'$ Depends on Group size only

• Log likelihood: $-\frac{NJ}{2} \log 2\pi - \frac{J}{2} \log |A| - \frac{1}{2} \sum_{j=1}^J \eta_{j(0)}' A^{-1} \eta_{j(0)} - \frac{J}{2} \sum_{k=1}^K (n_k - 1) \log \lambda_k - \frac{1}{2} \sum_{j=1}^J \sum_{k=1}^K \eta_{j(k)}' \eta_{j(k)} / \lambda_k$, where $\eta_j^* = Q' \tilde{Y}_j$

• Conjugate Priors:

$$A|C \sim IW(\nu, A_0), \quad \lambda_k \sim (iid) IG(a_\lambda, b_\lambda).$$

• Groups allocation: Mixture of Finite Mixtures (MFM) (Miller and Harrison, 2018)

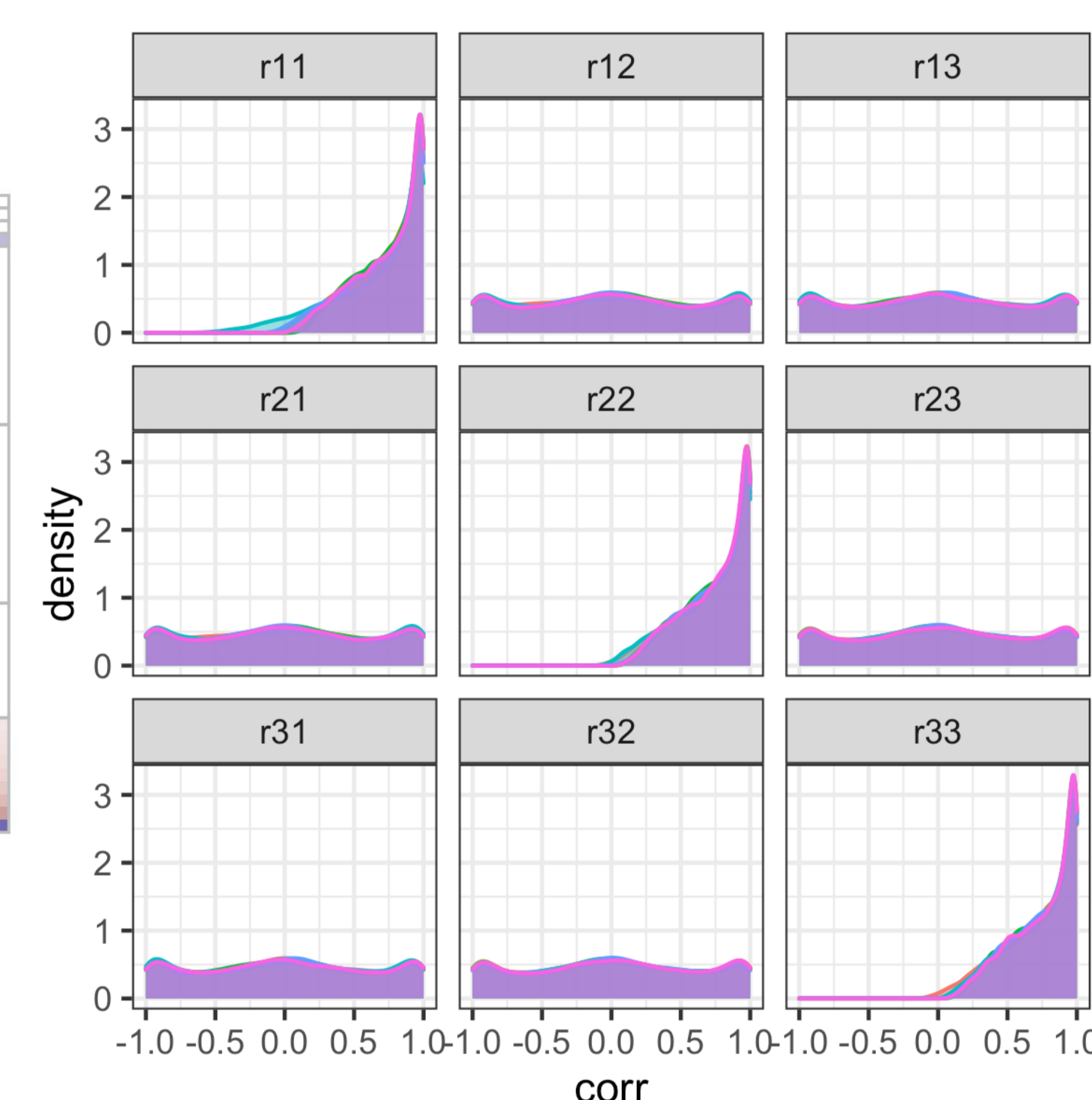
P : C denotes partition of $[N]$ induced by S_1, \dots, S_N :

$K \sim p_K$, where p_K is a p.m.f on $\{1, 2, \dots\}$, where we consider $K - 1 \sim \text{Pois}(1)$

Group allocation $(\pi_1, \dots, \pi_k) \sim \text{Dir}_k(\gamma, \dots, \gamma)$ given $K = k$

$S_i \in \{1, \dots, K\}$ $S_1, \dots, S_N \sim \pi$ (iid) given π

Numerical Experiments

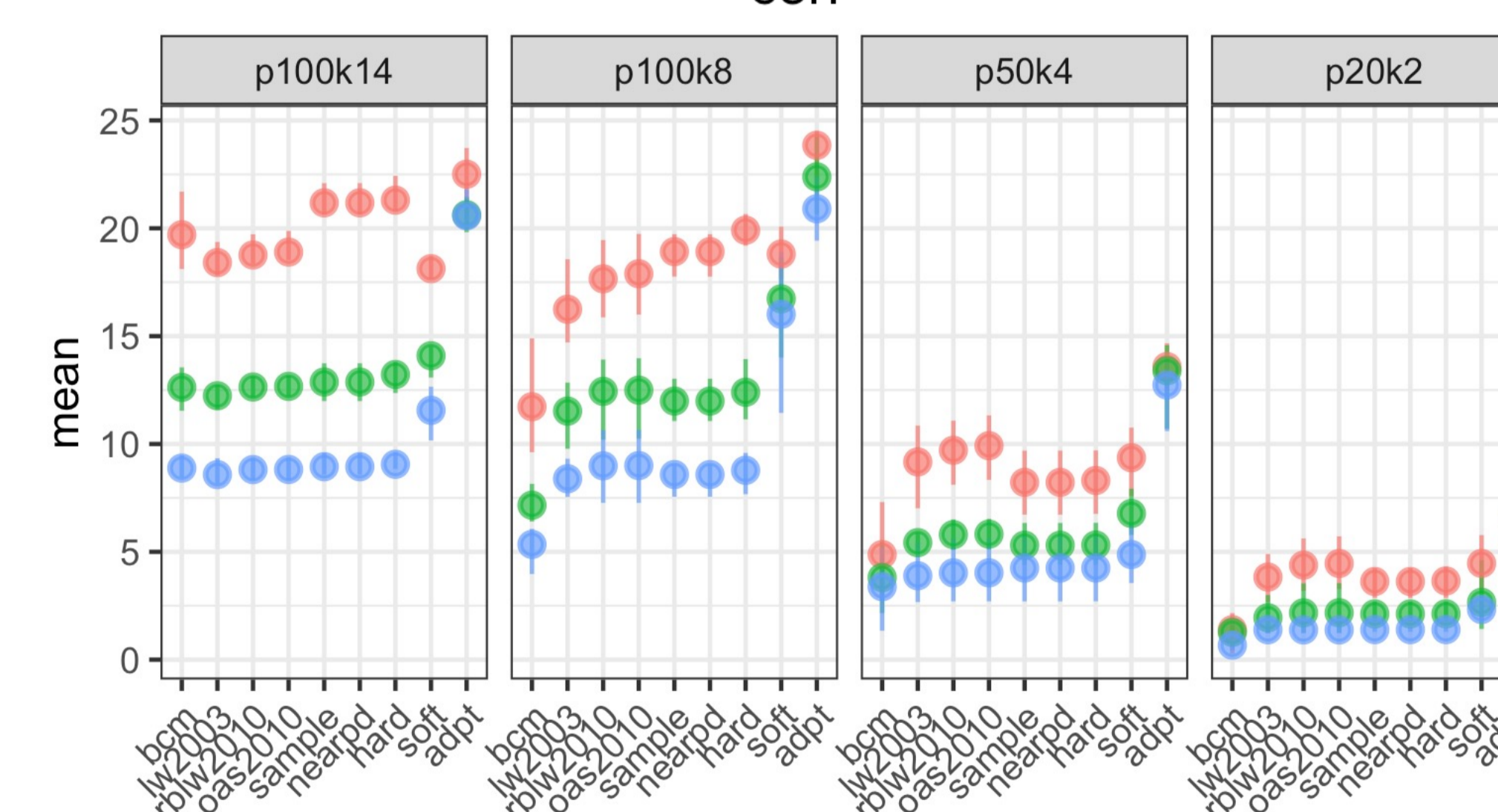


- Non-informative priors:
 - (1) invariant to group size
 - (2) between-group: uniformly distributed
 - (3) within-group: positive, relatively high

- Scale with group size:

$$\nu = K, A_{0(kk)} = n_k, \quad \lambda_k^{-1} \sim Ga(20, 10)$$

Fig. 2: Examples of induced priors for block correlation under different group allocation



- Estimation accuracy: BCM outperforms other alternatives except for situations with large p/k ratio (measured by Frobenius Dist)

- Grouping:

BCM recovers the true block structure in a decent way (smoothing/denoise) even under small n large p cases. ($p=100, n=20$)

