1 General Notations

- N: Number of users
- n: Number of items, $n = \begin{cases} 2m-1, & \text{if n is odd} \\ 2m, & \text{otherwise} \end{cases}$
- $\boldsymbol{R}^1, ..., \boldsymbol{R}^N$: full rankings given by the users
- $\{i_1, ..., i_n\}$: a set of ranking that determines which item to be sampled first. i.e. $i_j = 1$ means the j-th item is to be sampled first
- $\{o_1, ..., o_n\}$: a set of ordering that corresponds to (one-to-one relationship) $\{i_1, ..., i_n\}$ s.t. $i_{o_1} = 1$
- $\boldsymbol{R}^j = \{R_1^j, ..., R_{n,}^j\} \sim \text{Mallows}(\boldsymbol{\rho}^0, \alpha^0)$
- $\boldsymbol{\rho}^0 \leftrightarrow \boldsymbol{o}^0$ s.t. ${\rho^0}^{-1}(m) = o_m^0$
- $P(\boldsymbol{\rho}|\boldsymbol{R}^1, ..., \boldsymbol{R}^N, \alpha^o)$: Mallows posterior
- $q(\tilde{\boldsymbol{\rho}}| \ldots)$: pseudolikelihood that approxiamtes the Mallows posterior
- $q(\tilde{\boldsymbol{\rho}}|i_1, ..., i_n, \alpha^0)$
$= q(\tilde{\rho}_{o_1}|\alpha^0, o_1) \cdot q(\tilde{\rho}_{o_2}|\alpha^0, o_2, \tilde{\rho}_{o_1}) \cdot \ldots \cdot q(\tilde{\rho}_{o_{n-1}}|\alpha^0, o_{n-1}, \tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{n-2}}) \cdot q(\tilde{\rho}_{o_n}|\alpha^0, o_n, \tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{n-1}})$
- $q(\tilde{\rho}_{o_1}|\alpha^0, o_1) = \dfrac{\exp\{-\frac{\alpha_0}{n}\sum_{j=1}^{N} d(R_{o_1}^j, \tilde{\rho}_{o_1})\}\mathbb{1}_{\tilde{\rho}_{o_1} \in \{1,\ldots,n\}}}{\sum_{\tilde{r}_{o_1} \in \{1,..,n\}} \exp\{-\frac{\alpha_0}{n}\sum_{j=1}^{N} d(R_{o_1}^j, \tilde{r}_{o_1})\}}$
- $q(\tilde{\rho}_{o_k}|\alpha^0, o_k, \tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{k-1}}) = \dfrac{\exp\{-\frac{\alpha_0}{n}\sum_{j=1}^{N} d(R_{o_k}^j, \tilde{\rho}_{o_k})\}\mathbb{1}_{\tilde{\rho}_{o_k} \in \{1,..,n\} \setminus \{\tilde{\rho}_{o_1}, \ldots, \tilde{\rho}_{o_{k-1}}\}}}{\sum_{\tilde{r}_{o_k} \in \{1,..,n\} \setminus \{\tilde{\rho}_{o_1}, \ldots, \tilde{\rho}_{o_{k-1}}\}} \exp\{-\frac{\alpha_0}{n}\sum_{j=1}^{N} d(R_{o_k}^j, \tilde{r}_{o_k})\}}$ for $k = 2, ..., n$
- $\mathcal{V}_{\boldsymbol{\rho}^o} = \begin{cases} \{\boldsymbol{r} \in \mathcal{P}_n : r_{o_m^0} = 1, r_{o_{m\pm k}^0} \in \{2k, 2k+1\}, k = 1, ..., m-1\}, & \text{if n is odd} \\ \{\boldsymbol{r} \in \mathcal{P}_n : \{r_{o_{m-k}^0}, r_{o_{m+k+1}^0}\} \in \{2k+1, 2k+2\}, k = 0, ..., m\}, & \text{if n is even} \end{cases}$

2 Theorem 0

As $N \to \infty$, $\boldsymbol{\rho}^0 \to rank(\mathbb{E}[R_1], ..., \mathbb{E}[R_n]) \to rank(\frac{1}{N}\sum_{j=0}^{N} R_1^j, ..., \frac{1}{N}\sum_{j=0}^{N} R_n^j)$

It is proven that $\mathbb{E}[R_{o_j^0}] < \mathbb{E}[R_{o_k^0}]\ \forall j < k$ and $\alpha^0 > 0$. Therefore, as the number of users $N \to \infty$, the exact value of $\boldsymbol{\rho}^0$ can be inferred from the data by taking the marginal mean of each item and rank them according to the marginal means.

3 Theorem 1

$\lim_{N\to\infty} \arg\min_{g \in \mathcal{D}_{\boldsymbol{\rho}^0}} KL(P(\boldsymbol{\rho}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N)|| \sum_{\{i_1,...,i_n\}\in\mathcal{P}_n} q(\tilde{\boldsymbol{\rho}}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N, i_1, ..., i_n) g(i_1, ..., i_n|\boldsymbol{\rho}^0)$
$= g^*(i_1, ..., i_n|\mathcal{V}_{\boldsymbol{\rho}^0})$,
where

- $\mathcal{D}_{\boldsymbol{\rho}^0}$ is a set of all distrbutions on the space of permutation $\mathcal{P}_n$, which depends on $\boldsymbol{\rho}^0$, i.e., $\mathcal{D}_{\boldsymbol{\rho}^0}$={what is a good notation of this??}
- $g^*(i_1, ..., i_n|\mathcal{V}_{\boldsymbol{\rho}^0})$ is a distribution whose density is concentrated on $\boldsymbol{\rho}^0$, i.e.
$\begin{cases} g^*(i_1, ..., i_n|\mathcal{V}_{\boldsymbol{\rho}^0}) = |\mathcal{V}_{\boldsymbol{\rho}^0}|^{-1} > 0, & \text{if}\{i_1, ..., i_n\} \in \mathcal{V}_{\boldsymbol{\rho}^0} \\ g^*(i_1, ..., i_n|\mathcal{V}_{\boldsymbol{\rho}^0}) = 0, & \text{if}\{i_1, ..., i_n\} \notin \mathcal{V}_{\boldsymbol{\rho}^0} \end{cases}$

explanation: for a set of distributions g, which are defined the space of permutation of n items, i.e.$\mathcal{P}_n$, the distribution g^* that minimizes the KL-divergence betweeeh the Mallows posterior and the pseudolikelihood defined above, is a uniform distribution with its density concentrated on $\mathcal{V}_{\boldsymbol{\rho}^o}$

4 Theorem 2

For a given $N < \infty$, $\hat{\boldsymbol{\rho}}^0$ is defined as $rank(\frac{1}{N}\sum_{j=0}^{N} R_1^j, ..., \frac{1}{N}\sum_{j=0}^{N} R_n^j)$. $\hat{\boldsymbol{\rho}}^0 \neq \boldsymbol{\rho}^0$. The corresponding "$\mathcal{V}$-like" set is notated as $\mathcal{V}_{\hat{\boldsymbol{\rho}}^0}$.

$\exists\sigma \geq 0$,

KL $(P(\boldsymbol{\rho}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N)|| \sum_{\{i_1,...,i_n\}\in\mathcal{P}_n} q(\tilde{\boldsymbol{\rho}}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N, i_1, ..., i_n) g^*(i_1, ..., i_n|\mathcal{V}_{\hat{\boldsymbol{\rho}}^0)} \geq$
KL $(P(\boldsymbol{\rho}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N)|| \sum_{\{i_1,...,i_n\}\in\mathcal{P}_n} q(\tilde{\boldsymbol{\rho}}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N, i_1, ..., i_n) g'(i_1, ..., i_n|\mathcal{V}_{\hat{\boldsymbol{\rho}}^0}, \sigma) \geq$
$\lim_{N\to\infty}$ KL $(P(\boldsymbol{\rho}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N)|| \sum_{\{i_1,...,i_n\}\in\mathcal{P}_n} q(\tilde{\boldsymbol{\rho}}|\alpha^0, \boldsymbol{R}^1, ..., \boldsymbol{R}^N, i_1, ..., i_n) g^*(i_1, ..., i_n|\mathcal{V}_{\boldsymbol{\rho}^0})$,
where

- $\hat{\boldsymbol{v}} \sim \mathcal{U}(\hat{\boldsymbol{v}}|\mathcal{V}_{\hat{\rho}_0})$
- $i'_i \sim \mathcal{N}(i'_i|\hat{v}_i, \sigma)$ for $i = 1, ..., n$
- $i_1, ..., i_n = rank(i'_1, ..., i'_n)$,

and $g'(i_1, ..., i_n|\mathcal{V}_{\hat{\boldsymbol{\rho}}^0}) = \sum_{\hat{\boldsymbol{v}} \in \mathcal{V}_{\hat{\boldsymbol{\rho}}^0}} \mathcal{U}(\hat{\boldsymbol{v}}|\mathcal{V}_{\hat{\boldsymbol{\rho}}^0}) \prod_{i=1}^{n} \mathcal{N}(i'_i|\hat{v}_i, \sigma) \cdot 1$

Explanation: as N is limited, $\boldsymbol{\rho}^0$, and therefore, $\mathcal{V}_{\boldsymbol{\rho}^0}$ cannot be accurately inferred from the data. We can however, sample for $i_1, ..., i_n$ by sampling for each item i from a univariate Gaussian distribution centred on $\hat{v}_i$ with a fixed variance σ for all items, and then rank the resulting "scores" to convert it back to rankings. By doing so, we can achieve a smaller KL divergence to the Mallows posterior, compared to not introducing the Gaussian noise.

5 Theorem 3

$$\sigma = \begin{cases} 0, & \text{if } \delta(\alpha, n, N) \leq \delta^* \\ f(\alpha, n, N), & \text{otherwise} \end{cases}$$

Explanation: With the usage of $g'(i_1, ..., i_n|\mathcal{V}_{\hat{\boldsymbol{\rho}}^0})$, the value of σ which minimizes the KL-divergence between the Mallows posterior and the resulted Pseudolikelihood should be 0 when $\delta(\alpha, n, N) \geq \delta^*$. Beyond this point, the optimal choice of σ should be greater than 0, and it follows a function $f(\alpha, n, N)$

6 Theorem 4

as $N \to \infty, \delta^* \to \max\delta(\alpha, n, N)$, $\forall \alpha > 0, n \geq 1$