1 General Notations

- \bullet N: Number of users
- n: Number of items, $n = \begin{cases} 2m-1, & \text{if n is odd} \\ 2m, & \text{otherwise} \end{cases}$
- $\mathbb{R}^1, ..., \mathbb{R}^N$: full rankings given by the users
- $\mathbf{R}^j = \{R_1^j, ..., R_n^j,\} \sim \text{Mallows}(\boldsymbol{\rho}^0, \alpha^0)$
- $P(\rho|\mathbf{R}^1,...,\mathbf{R}^N,\alpha^o)$: Mallows posterior
- $\{i_1, ..., i_n\}$: a ranking of n items that determines the sequence following which the items are to be sampled. i.e. $i_j = k$ indicates that item j is the k-th item is to be sampled
- $\{o_1,...,o_n\}$: an ordering of n items that corresponds to $\{i_1,...,i_n\}$ s.t. $i_{o_k}=k$. $\{o_1,...,o_n\}$ and $\{i_1,...,i_n\}$ have a one-to-one relationship
- $\sum_{\{i_1,...,i_n\}\in\mathcal{P}_n} q(\tilde{\boldsymbol{\rho}}|i_1,...,i_n,\alpha_0,\boldsymbol{R}^1,...,\boldsymbol{R}^N)\cdot g(i_1,...,i_n|...)$: pseudolikelihood that approxiamtes the Mallows posterior
- $\begin{array}{l} \bullet \ \ q(\tilde{\pmb{\rho}}|i_1,...,i_n,\alpha^0,\pmb{R}^1,...,\pmb{R}^N) \\ = q(\tilde{\rho}_{o_1}|\alpha^0,o_1,R^1_{o_1},...,R^N_{o_1}) \cdot q(\tilde{\rho}_{o_2}|\alpha^0,o_2,\tilde{\rho}_{o_1}R^1_{o_2},...,R^N_{o_2}) \cdot ... \cdot \\ q(\tilde{\rho}_{o_{n-1}}|\alpha^0,o_{n-1},\tilde{\rho}_{o_1},...,\tilde{\rho}_{o_{n-2}},R^1_{n-1},...,R^N_{n-1}) \cdot q(\tilde{\rho}_{o_n}|\alpha^0,o_n,\tilde{\rho}_{o_1},...,\tilde{\rho}_{o_{n-1}},R^1_n,...,R^N_n) \end{array}$

$$-\ q(\tilde{\rho}_{o_1}|\alpha^0,o_1,R^1_{o_1},...,R^N_{o_1}) = \frac{\exp\{-\frac{\alpha_0}{n}\sum\limits_{j=1}^N d(R^j_{o_1},\tilde{\rho}_{o_1})\}\mathbb{1}_{\tilde{\rho}_{o_1}\in\{1,...,n\}}}{\sum\limits_{\tilde{r}_{o_1}\in\{1,...,n\}} \exp\{-\frac{\alpha_0}{n}\sum\limits_{j=1}^N d(R^j_{o_1},\tilde{r}_{o_1})\}}$$

$$- \ q(\tilde{\rho}_{o_k} | \alpha^0, o_k, \tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{k-1}}, R^1_{o_k}, ..., R^N_{o_k}) = \frac{\exp\{-\frac{\alpha_0}{n} \sum\limits_{j=1}^N d(R^j_{o_k}, \tilde{\rho}_{o_k})\} \mathbb{1}_{\tilde{\rho}_{o_k} \in \{1, ..., n\} \setminus \{\tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{k-1}}\}}}{\sum\limits_{\tilde{r}_{o_k} \in \{1, ..., n\} \setminus \{\tilde{\rho}_{o_1}, ..., \tilde{\rho}_{o_{k-1}}\}} \exp\{-\frac{\alpha_0}{n} \sum\limits_{j=1}^N d(R^j_{o_k}, \tilde{r}_{o_k})\}}$$
 for $k = 2, ..., n$

•
$$\rho^0 \leftrightarrow \sigma^0$$
 s.t. $\rho^{0-1}(m) = o_m^0$

• Define the "v-function" $f_v(\cdot)$ such that $f_v(\rho^0) = \mathcal{V}_{\rho^0}$, where

$$-\ \mathcal{V}_{\boldsymbol{\rho}^o} = \begin{cases} \{ \boldsymbol{r} \in \mathcal{P}_n : r_{o_m^0} = 1, r_{o_{m \pm k}^0} \in \{2k, 2k + 1\}, k = 1, ..., m - 1\}, & \text{if n is odd} \\ \{ \boldsymbol{r} \in \mathcal{P}_n : \{ r_{o_{m - k}^0}, r_{o_{m + k + 1}^0} \} \in \{2k + 1, 2k + 2\}, k = 0, ..., m\}, & \text{if n is even} \end{cases}$$

2 Theorems and Lemmas

2.1

Lemma 2.1.1 Given there are odd number of items, i.e. n = 2m - 1. $\forall \alpha^0 \in (0, \infty)$,

1.
$$\mathbb{E}(R_{o_m^0}|\boldsymbol{\rho}_0,\alpha^0)=\rho_m^0=m$$

$$2. \ \forall j \in [1, m-2], \ j < \mathbb{E}[R_{o_{i}^{0}}|\rho^{0}, \alpha^{0}] < \mathbb{E}[R_{o_{i+1}^{0}}|\rho^{0}, \alpha^{0}] < m$$

3.
$$\forall j \in [m+2, 2m-1], \ m < \mathbb{E}[R_{o_{j-1}^0}|\boldsymbol{\rho}^0, \alpha^0] < \mathbb{E}[R_{o_j^0}|\boldsymbol{\rho}^0, \alpha^0] < j$$

Similarly, if n is even, i.e. n = 2m, $\forall \alpha^0 \in (0, \infty)$,

1.
$$\forall j \in [1, m-1], j < \mathbb{E}[R_{o_j^0}|\boldsymbol{\rho}^0, \alpha^0] < \mathbb{E}[R_{o_{j+1}^0}|\boldsymbol{\rho}^0, \alpha^0]$$

$$2. \ \forall j \in [m+2,2m], \ \mathbb{E}[R_{o_{i-1}^0}| \pmb{\rho}^0,\alpha^0] < \mathbb{E}[R_{o_i^0}| \pmb{\rho}^0,\alpha^0] < j$$

Note that for both cases, it satisfies that $\forall 1 \leq j < k \leq n \text{ and } \forall \alpha > 0, \ \mathbb{E}[R_{o_j^0}|\boldsymbol{\rho}^0,\alpha^0] < \mathbb{E}[R_{o_i^0}|\boldsymbol{\rho}^0,\alpha^0]$

Lemma 2.1.2 As
$$N \to \infty$$
, $\frac{1}{N} \sum_{i=1}^{N} R_i^j \to \mathbb{E}[R_i | \boldsymbol{\rho}^0, \alpha^0]$, $\forall i = 1, ..., n$

Definition 1 Given a vector of length n, i.e. $\{x_1,...,x_n\}$, the rank function $rank(x_1,...,x_n)$ is defined as $rank(x_1,...,x_n) = \{r_1,...,r_n\}$ such that $x_{(r_k)} = x_k$, $\forall k = 1,...,n$

Theorem 2.1.3 As
$$N \to \infty$$
, and $\forall \alpha > 0$,

$$rank(\frac{1}{N}\sum_{j=0}^{N}R_{1}^{j},...,\frac{1}{N}\sum_{j=0}^{N}R_{n}^{j}) \rightarrow rank(\mathbb{E}[R_{1}|\boldsymbol{\rho}^{0},\alpha_{0}],...,\mathbb{E}[R_{n}|\boldsymbol{\rho}^{0},\alpha_{0}]) = \boldsymbol{\rho}^{0}$$

That rephrase it, as N approaches infinity, the Mallows consensus parameter ρ^0 can be inferred from the data by taking the marginal mean for each item and then apply the rank function to these marginal means.

2.2

Theorem 2.2.1 For a function g defined on the space of permutation \mathcal{P}_n which can depend on ρ^0 ,

• \mathcal{D}_{ρ^0} is the set of all distributions on the space of permutation \mathcal{P}_n , which can depend on ρ^0

$$\begin{array}{l} \bullet \ \ g^*(i_1,...,i_n|\mathcal{V}_{\boldsymbol{\rho}^0}) \ \ is \ \ a \ \ distribution \ \ whose \ \ density \ is \ \ concentrated \ \ on \ \ \boldsymbol{\rho}^0, \ \ defined \ \ as \\ \left\{ \begin{aligned} g^*(i_1,...,i_n|\mathcal{V}_{\boldsymbol{\rho}^0}) &= |\mathcal{V}_{\boldsymbol{\rho}^0}|^{-1} > 0, \quad \ \ if \ \{i_1,...,i_n\} \in \mathcal{V}_{\boldsymbol{\rho}^0}, \ \ where \ |\mathcal{V}_{\boldsymbol{\rho}^0}| &= \begin{cases} 2^{m-1}, & \ \ if \ n \ \ is \ \ odd \\ 2^m, & \ \ otherwise \end{aligned} \right. \\ \left\{ g^*(i_1,...,i_n|\mathcal{V}_{\boldsymbol{\rho}^0}) &= 0, & \ \ \ if \ \{i_1,...,i_n\} \notin \mathcal{V}_{\boldsymbol{\rho}^0}, \end{aligned} \right.$$

That is to say, for a set of distributions g, which are defined on the space of permutation of n items \mathcal{P}_n , the distribution g^* that minimizes the KL-divergence between the Mallows posterior and the pseudolikelihood defined above, is a uniform distribution with its density concentrated on \mathcal{V}_{ρ^o}

2.3

For a given
$$N < \infty$$
, define $\hat{\boldsymbol{\rho}}^0$ as $rank(\frac{1}{N}\sum_{j=0}^N R_1^j,...,\frac{1}{N}\sum_{j=0}^N R_n^j)$ and $\mathcal{V}_{\hat{\boldsymbol{\rho}}^0} = f_v(\hat{\boldsymbol{\rho}}^0)$.

Theorem 2.3.1 $\exists \sigma \geq 0 \text{ and } g'(i_1,...,i_n|\mathcal{V}_{\hat{\rho}^0},\sigma) \text{ such that }$

$$KL \left(P(\boldsymbol{\rho}|\alpha^{0}, \boldsymbol{R}^{1}, ..., \boldsymbol{R}^{N})||\sum_{\{i_{1}, ..., i_{n}\} \in \mathcal{P}_{n}} q(\tilde{\boldsymbol{\rho}}|\alpha^{0}, \boldsymbol{R}^{1}, ..., \boldsymbol{R}^{N}, i_{1}, ..., i_{n})g^{*}(i_{1}, ..., i_{n}|\mathcal{V}_{\hat{\boldsymbol{\rho}}^{0}}) \geq KL \left(P(\boldsymbol{\rho}|\alpha^{0}, \boldsymbol{R}^{1}, ..., \boldsymbol{R}^{N})||\sum_{\{i_{1}, ..., i_{n}\} \in \mathcal{P}_{n}} q(\tilde{\boldsymbol{\rho}}|\alpha^{0}, \boldsymbol{R}^{1}, ..., \boldsymbol{R}^{N}, i_{1}, ..., i_{n})g'(i_{1}, ..., i_{n}|\mathcal{V}_{\hat{\boldsymbol{\rho}}^{0}}, \sigma)\right)$$

where

- $\hat{\boldsymbol{v}} \sim g^*(\hat{\boldsymbol{v}}|\mathcal{V}_{\hat{\boldsymbol{\rho}^0}})$
- $x_i \sim \mathcal{N}(x_i|\hat{v}_i, \sigma)$ for i = 1, ..., n

•
$$i_1, ..., i_n \sim \mathcal{F}_r(i_1, ..., i_n | x_1, ..., x_n)$$
, where $\mathcal{F}_r = \begin{cases} 1, & \text{if } i_1, ..., i_n = rank(x_1, ..., x_n) \\ 0, & \text{otherwise} \end{cases}$

and
$$g'(i_1, ..., i_n | \mathcal{V}_{\hat{\rho}^0}, \sigma) = \sum_{\hat{v} \in \mathcal{V}_{\hat{\rho}^0}} \{ g^*(\hat{v} | \mathcal{V}_{\hat{\rho}^0}) \int_{\mathbf{x}} \mathcal{F}_r(i_1, ..., i_n | x_1, ..., x_n) \prod_{i=1}^n \mathcal{N}(x_i | \hat{v}_i, \sigma) d\mathbf{x} \}$$

As N is limited, ρ^0 , and therefore, \mathcal{V}_{ρ^0} usually 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 centeredd on \hat{v}_i with a fixed variance σ for all items, and then obtain a ranking by using the rank function. By doing so, a smaller KL divergence from the Mallows posterior can be obtained, compared to not introducing the variations.

2.4

Theorem 2.4.1 With the usage of $g'(i_1,...,i_n|\mathcal{V}_{\hat{\rho}^0},\sigma)$, the value of σ that minimizes the KL-divergence between the Mallows posterior and the resulted pseudolikelihood is $\sigma = \begin{cases} 0, & \text{if } \delta(\alpha, n, N) \leq \delta^* \\ f(\alpha, n, N), & \text{otherwise} \end{cases}$

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

In other words, σ 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 $f(\alpha, n, N)$.

2.5

Theorem 2.5.1 As $N \to \infty, \sigma = 0 \ \forall \alpha > 0, n \ge 1$