



# **Dimensionality Reduction and (Bucket) Ranking: a Mass Transportation Approach**

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# Outline

Introduction

Dimensionality Reduction on  $\mathcal{G}_n$

Empirical Distortion Minimization

Numerical Experiments on a Real-world Dataset



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- ▶ Distribution  $P$  on  $\mathfrak{S}_n$ :  $n! - 1$  parameters



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- ▶ Problem: no vector space structure for permutations



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Partial order: " $i$  is ranked lower than  $j$  in  $\mathcal{C}$ " if  $\exists k < l$  s.t.  $(i, j) \in \mathcal{C}_k \times \mathcal{C}_l$ .





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$P' \in \mathbf{P}_{\mathcal{C}}$  described by  $d_{\mathcal{C}} = \prod_{k \leq K} \#\mathcal{C}_k! - 1 \leq n! - 1$  parameters

## Background on Consensus Ranking

Consensus ranking (or "ranking aggregation"): summarize permutations  $\sigma_1, \dots, \sigma_N$  by a consensus/median ranking  $\sigma^* \in \mathfrak{S}_n$  by solving:

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If  $\Sigma_1, \dots, \Sigma_N$  i.i.d. sampled from  $P$  (Korba et al., 2017), solve:

$$\min_{\sigma \in \mathfrak{S}_n} \mathbb{E}_{\Sigma \sim P} [d(\Sigma, \sigma)].$$



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Unique Kemeny median  $\sigma_P^*$  if  $P$  strictly stochastically transitive:

- ▶  $p_{i,j} \geq 1/2$  and  $p_{j,k} \geq 1/2 \Rightarrow p_{i,k} \geq 1/2$
- ▶  $p_{i,j} \neq 1/2$  for all  $i < j$
- ▶ given by Copeland ranking

$$\sigma_P^*(i) = 1 + \sum_{j \neq i} \mathbb{I}\{p_{i,j} < 1/2\}.$$



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Problem: generalization for any bucket order.





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## Definition

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- ▶ Focus on  $d = d_{\tau}$  and  $q = 1$ .

## Distortion measure

A bucket order  $\mathcal{C}$  represents well  $P$  if small distortion  $\Lambda_P(\mathcal{C})$ .

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Explicit expression for  $\Lambda_P(\mathcal{C})$ :

### Proposition

$$\Lambda_P(\mathcal{C}) = \sum_{1 \leq k < l \leq K} \sum_{(i,j) \in \mathcal{C}_k \times \mathcal{C}_l} p_{j,i}$$



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- ▶ Empirical distortion of any bucket order  $\mathcal{C}$ :

$$\hat{\Lambda}_N(\mathcal{C}) = \Lambda_{\hat{P}_N}(\mathcal{C}) = \sum_{1 \leq k < l \leq K} \sum_{(i,j) \in \mathcal{C}_k \times \mathcal{C}_l} \hat{p}_{j,i}. \quad (1)$$

## Rate bound

Empirical distortion minimizer  $\widehat{\mathbf{C}}_{K,\lambda}$  is solution of:

$$\min_{\mathbf{C} \in \mathbf{C}_{K,\lambda}} \widehat{\Lambda}_N(\mathbf{C}),$$

where  $\mathbf{C}_{K,\lambda}$  set of bucket orders  $\mathbf{C}$  of size  $K$  and shape  $\lambda$  (i.e.  $\#C_k = \lambda_k$  for all  $1 \leq k \leq K$ ).

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### Theorem

*For all  $\delta \in (0, 1)$ , we have with probability at least  $1 - \delta$ :*

$$\Lambda_P(\hat{\mathbf{C}}_{K,\lambda}) - \inf_{\mathbf{C} \in \mathbf{C}_{K,\lambda}} \Lambda_P(\mathbf{C}) \leq \beta(n, \lambda) \times \sqrt{\frac{\log(\frac{1}{\delta})}{N}}.$$



## The Strong Stochastic Transitive Case

Assume that  $P$  is strongly (and strictly) stochastically transitive  
i.e.:

$$p_{i,j} \geq 1/2 \text{ and } p_{j,k} \geq 1/2 \Rightarrow p_{i,k} \geq \max(p_{i,j}, p_{j,k}).$$

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- (i)  $\Lambda_P(\cdot)$  has a unique minimizer  $\mathcal{C}^{*(K,\lambda)}$  over  $\mathbf{C}_{K,\lambda}$ .
- (ii)  $\mathcal{C}^{*(K,\lambda)}$  is the unique bucket order in  $\mathbf{C}_{K,\lambda}$  agreeing with the Kemeny median.

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Consequence: agglomerative algorithm.



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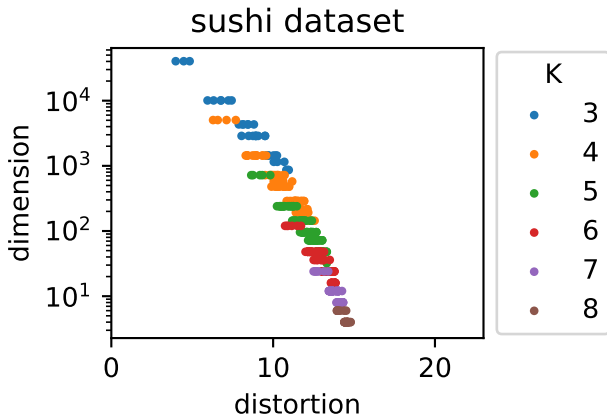
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# Experiments

Sushi dataset (Kamishima, 2003):

- ▶  $n = 10$  sushi dishes
- ▶  $N = 5000$  full rankings.



Thank you!