Controlling the distance to the Kemeny consensus without computing it

Eric Sibony Yunlong Jiao Anna Korba

LTCI UMR 5141, Telecom ParisTech/CNRS, Mines ParisTech

ICML 2016

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

The ranking aggregation problem can be encoutered in many fields of the scientific literature

- Elections in Social choice theory
- Meta search engines
- Competitions rankings
- Analysis of biological data
- Natural Language Processing

Problem:

How to summarize a collection of rankings into one ranking?

Input

- Set of items: $[\![n]\!] := \{1, ..., n\}$
- *N* Rankings of the form : $i_1 \succ \cdots \succ i_n$

Output

A global order ("consensus") σ^* on the *n* objects.

Ranking $i_1 \succ \cdots \succ i_n$ on $[n] \iff$ permutation σ on [n] s.t. $\sigma(i_j) = j$.

Ranking $i_1 \succ \cdots \succ i_n$ on $[n] \iff$ permutation σ on [n] s.t. $\sigma(i_j) = j$.

What permutation $\sigma^* \in \mathfrak{S}_n$ best represents a given a collection of permutations $(\sigma_1, \ldots, \sigma_N) \in \mathfrak{S}_n^N$?

Ranking $i_1 \succ \cdots \succ i_n$ on $[n] \iff$ permutation σ on [n] s.t. $\sigma(i_j) = j$.

What permutation $\sigma^* \in \mathfrak{S}_n$ best represents a given a collection of permutations $(\sigma_1, \ldots, \sigma_N) \in \mathfrak{S}_n^N$?

Definition (Consensus ranking (Kemeny, 1959))

A permutation $\sigma^* \in \mathfrak{S}_n$ is a best representative of the collection $(\sigma_1, \ldots, \sigma_N) \in \mathfrak{S}_n^N$ with respect to a metric d on \mathfrak{S}_n if it is a solution of :

$$\min_{\sigma \in \mathfrak{S}_n} \sum_{t=1}^N d(\sigma, \sigma_t).$$

Kemeny's rule

Definition (*Kendall's distance*)

The Kendalls tau distance between two permutations is equal to the number of their pairwise disagreements:

$$d_{\mathcal{KT}}(\sigma,\pi) = \sum_{\{i,j\} \subset \llbracket n \rrbracket} \mathbb{I}\{\sigma \text{ and } \pi \text{ disagree on } \{i,j\}\}$$

▲□▶ ▲□▶ ▲□▶ ▲□▶ ▲□ ● ● ●

Example

$$\sigma = 123 (1 \succ 2 \succ 3)$$

$$\pi = 231 (2 \succ 3 \succ 1)$$

 \rightarrow number of desagreements = on 2 pairs (12,13).

Kemeny's rule

Definition (Kendall's distance)

The Kendalls tau distance between two permutations is equal to the number of their pairwise disagreements:

$$d_{\mathcal{KT}}(\sigma,\pi) = \sum_{\{i,j\} \subset \llbracket n \rrbracket} \mathbb{I}\{\sigma \text{ and } \pi \text{ disagree on } \{i,j\}\}$$

Example

$$\sigma = 123 (1 \succ 2 \succ 3)$$

 $\pi = 231 (2 \succ 3 \succ 1)$

 \rightarrow number of desagreements = on 2 pairs (12,13).

Definition (Kemeny's rule)

$$\min_{\sigma \in \mathfrak{S}_n} \sum_{t=1}^{N} d_{KT}(\sigma, \sigma_t)$$
(1)

Kemeny's rule

- Social choice justification: Satisfies many voting properties, such as the Condorcet criterion: if a candidate is preferred to all others in pairwise comparisons then it is the winner [Young and Levenglick, 1978]
- Statistical justification: Outputs the maximum likelihood estimator under the Mallows model [Young, 1988]
- Main drawback: It is NP-hard in the number of votes N [Bartholdi et al., 1989] even for n = 4 candidates [Dwork et al., 2001].

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

Contribution

Previous contributions

- General guarantees for approximation procedures
- Bounds on the approximation cost of procedures
- Conditions for the exact Kemeny aggregation to become tractable

Contribution

Previous contributions

- General guarantees for approximation procedures
- Bounds on the approximation cost of procedures
- Conditions for the exact Kemeny aggregation to become tractable

Our approach

- Set of items $\llbracket n \rrbracket := \{1, \ldots, n\}$
- A rankings dataset $\mathcal{D}_N = (\sigma_1, \dots, \sigma_N) \in \mathfrak{S}_n^N$
- Let σ ∈ G_n a permutation, typically out put by a computationally efficient aggregation procedure on D_N.

Can we give an upper bound $d(\sigma, \sigma^*)$ between σ and a Kemeny consensus, by using only tractable quantities?

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

◆□▶ ◆□▶ ◆目▶ ◆目▶ 目 のへで

Kemeny embedding

The Kemeny embedding is the mapping $\phi : \mathfrak{S}_n \to \mathbb{R}^{\binom{n}{2}}$ defined by:

$$\phi: \sigma \mapsto \left(\begin{array}{c} \vdots \\ \operatorname{sign}(\sigma(i) - \sigma(j)) \\ \vdots \end{array}\right)_{1 \le i < j \le n}$$

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

where sign(x) = 1 if $x \ge 0$ and 1 otherwise.

Example

$$123 \mapsto \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \xrightarrow[]{\rightarrow} \text{ pair } 12 \\ \xrightarrow[]{\rightarrow} \text{ pair } 13 \\ \xrightarrow[]{\rightarrow} \text{ pair } 23 \end{pmatrix}, 132 \mapsto \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix} \xrightarrow[]{\rightarrow} \text{ pair } 13 \\ \xrightarrow[]{\rightarrow} \text{ pair } 13 \\ \xrightarrow[]{\rightarrow} \text{ pair } 23 \end{pmatrix}$$

Kemeny aggregation in $\mathbb{R}^{\binom{n}{2}}$

Definition (Mean embedding)

For $D_N = (\sigma_1, \ldots, \sigma_N) \in \mathfrak{S}_n^N$, we define the barycenter:

$$\phi(\mathcal{D}_N) := \frac{1}{N} \sum_{t=1}^N \phi(\sigma_t).$$

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

Kemeny aggregation in $\mathbb{R}^{\binom{n}{2}}$

Definition (Mean embedding)

For $D_N = (\sigma_1, \ldots, \sigma_N) \in \mathfrak{S}_n^N$, we define the barycenter:

$$\phi\left(\mathcal{D}_{N}\right) := \frac{1}{N} \sum_{t=1}^{N} \phi\left(\sigma_{t}\right).$$

Proposition (Barthelemy & Monjardet (1981))

For all
$$\sigma, \sigma' \in \mathfrak{S}_n$$
,

$$\|\phi(\sigma)\| = \sqrt{rac{n(n-1)}{2}}$$
 and $\|\phi(\sigma) - \phi(\sigma')\|^2 = 4d(\sigma,\sigma'),$

and for any dataset $\mathcal{D}_N = (\sigma_1, \dots, \sigma_N) \in \mathfrak{S}_n^N$, Kemeny aggregation (1) is equivalent to the minimization problem

$$\min_{\sigma \in \mathfrak{S}_n} \|\phi(\sigma) - \phi(\mathcal{D}_N)\|^2 \tag{2}$$

Illustration

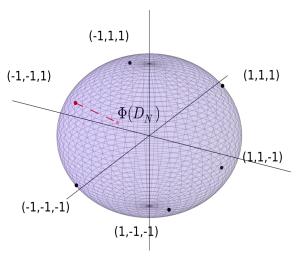


Figure: Kemeny aggregation for n = 3.

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 の�?

Kemeny aggregation naturally decomposes in two steps:

1. Compute the barycenter $\phi(\mathcal{D}_N) \in \mathbb{R}^{\binom{n}{2}}$ (complexity $O(Nn^2)$)

2. Find the consensus σ^* solution of problem (2)

Main result

For $\sigma \in \mathfrak{S}_n$, we define the angle $\theta_N(\sigma)$ between $\phi(\sigma)$ and $\phi(\mathcal{D}_N)$ by:

$$\cos(\theta_N(\sigma)) = \frac{\langle \phi(\sigma), \phi(\mathcal{D}_N) \rangle}{\|\phi(\sigma)\| \|\phi(\mathcal{D}_N)\|},$$

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 の�?

with $0 \leq \theta_N(\sigma) \leq \pi$.

Main result

For $\sigma \in \mathfrak{S}_n$, we define the angle $\theta_N(\sigma)$ between $\phi(\sigma)$ and $\phi(\mathcal{D}_N)$ by:

$$\cos(heta_N(\sigma)) = rac{\langle \phi(\sigma), \phi(\mathcal{D}_N)
angle}{\|\phi(\sigma)\| \|\phi(\mathcal{D}_N)\|}$$

with $0 \leq \theta_N(\sigma) \leq \pi$.

Theorem

Let $\mathcal{D}_N \in \mathfrak{S}_n^N$ be a dataset, \mathcal{K}_N the set of Kemeny consensuses and $\sigma \in \mathfrak{S}_n$ a permutation. For any $k \in \{0, \ldots, \binom{n}{2} - 1\}$, one has the following implication:

$$\cos(heta_N(\sigma)) > \sqrt{1 - rac{k+1}{\binom{n}{2}}} \quad \Rightarrow \quad \max_{\sigma^* \in \mathcal{K}_N} d(\sigma, \sigma^*) \leq k.$$

Method

We define:

$$k_{\min}(\sigma; \mathcal{D}_N) = \left\lfloor \binom{n}{2} \sin^2(\theta_N(\sigma)) \right\rfloor.$$
(3)

the minimal $k \in \{0, \dots, \binom{n}{2} - 1\}$ verifying the theorem condition.

Two steps:

- Compute $k_{min}(\sigma; \mathcal{D}_N)$ with Formula (3).
- Then by Theorem 15, d(σ, σ^{*}) ≤ k_{min}(σ; D_N) for all Kemeny consenus σ^{*} ∈ K_N.

Application on the sushi dataset

Table: Summary of a case-study on the validity of the method with the sushi dataset (N = 5000, n = 10). Rows are ordered by increasing k_{min} (or decreasing cosine) value.

Voting rule	$\cos(\theta_N(\sigma))$	$k_{min}(\sigma)$
Borda	0.82	14
Copeland	0.82	14
QuickSort	0.82	14
Plackett-Luce	0.80	15
2-approval	0.74	20
1-approval	0.71	22
Pick-a-Perm	0.40	37
Pick-a-Random	0.28	41

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

Extended cost function

Kemeny aggregation:

$$\min_{\sigma\in\mathfrak{S}_n}C'_N(\sigma)=\|\phi(\sigma)-\phi(\mathcal{D}_N)\|^2.$$

Relaxed problem:

$$\min_{x\in\mathbb{S}}\mathcal{C}_N(x) := \|x - \phi(\mathcal{D}_N)\|^2.$$
(4)

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 のへぐ

Extended cost function

Kemeny aggregation:

$$\min_{\sigma\in\mathfrak{S}_n}C'_N(\sigma)=\|\phi(\sigma)-\phi(\mathcal{D}_N)\|^2.$$

Relaxed problem:

$$\min_{x\in\mathbb{S}}\mathcal{C}_N(x) := \|x - \phi(\mathcal{D}_N)\|^2.$$
(4)

For any $x \in \mathbb{S}$, by denoting *R* the radius of \mathbb{S} , one has:

$$\mathcal{C}_N(x) = R^2 + \|\phi(\mathcal{D}_N)\|^2 - 2R\|\phi(\mathcal{D}_N)\|\cos(\theta_N(x)).$$

The level sets of C_N are thus of the form $\{x \in S \mid \theta_N(x) = \alpha\}$, for $0 \le \alpha \le \pi$

Illustration

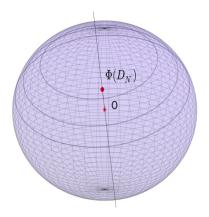


Figure: Level sets of C_N

(ロ)、(型)、(E)、(E)、 E) の(の)

Lemmas

Lemma (1) A Kemeny consensus of a dataset D_N is a permutation σ^* s.t:

$$\theta_N(\sigma^*) \leq \theta_N(\sigma)$$
 for all $\sigma \in \mathfrak{S}_n$.

We denote by $\mathcal{B}(x, r) = \{x' \in \mathbb{R}^{\binom{n}{2}} \mid ||x' - x|| < r\}$ the (open) ball of center x and radius r.

Lemma (2)

For $x \in \mathbb{S}$ and $r \ge 0$, one has:

$$\cos(heta_N(x)) > \sqrt{1 - rac{r^2}{4R^2}} \Rightarrow \min_{x' \in \mathbb{S} \setminus \mathcal{B}(x,r)} heta_N(x') > heta_N(x).$$

Illustration

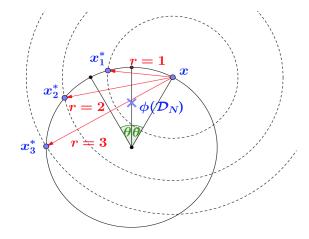


Figure: Illustration of Lemma 2 with *r* taking integer values (representing possible Kendall's tau distance).

Embedding of a ball

Lemma (3)
For
$$\sigma \in \mathfrak{S}_n$$
 and $k \in \{0, \dots, \binom{n}{2}\}$,
 $\phi(\mathfrak{S}_n \setminus B(\sigma, k)) \subset \mathbb{S} \setminus \mathcal{B}(\phi(\sigma), 2\sqrt{k+1})$

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

▲□▶ ▲圖▶ ▲臣▶ ▲臣▶ 三臣 - わへで

Applicability of the method

We denote by:

- n the number of alternatives
- $\mathcal{D}_N \in \mathfrak{S}_n^N$ any dataset
- ▶ r any voting rule, and by r(D_N) the consensuses of D_N given by r

We know that:

$$d(r(\mathcal{D}_N),\mathcal{K}_N) \leq k_{min}$$
 .

We study the tightness of the bound:

$$s(r, \mathcal{D}_N, n) := k_{min} - d(r(\mathcal{D}_N), \mathcal{K}_N).$$

Results

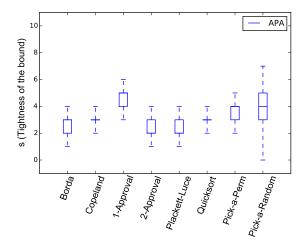


Figure: Boxplot of $s(r, D_N, n)$ over sampling collections of datasets shows the effect from different voting rules r with 500 bootstrapped pseudo-samples of the APA dataset (n = 5, N = 5738).

Predictability of the method

▶ When n grows, the exact Kemeny consensus K_N, hence s (r, D_N, n) quickly becomes computationally impermissible.

► Once we have an approximate ranking r(D_N) and k_{min} is identified via our method, the search scope for the exact Kemeny consensuses can be narrowed down to those permutations within a distance of k_{min} to r(D_N).

▶ Notably the total number of such permutations in \mathfrak{S}_n is upper bounded by $\binom{n+k_{min}-1}{k_{min}} << |\mathfrak{S}_n| = n!$ [Wang 2013].

Results

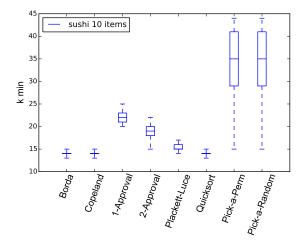


Figure: Boxplot of k_{min} over 500 bootstrapped pseudo-samples of the sushi dataset (n = 10, N = 5000).

・ロト ・聞ト ・ヨト ・ヨト

æ

Outline

Ranking aggregation and Kemeny's rule

Controlling the distance to a Kemeny consensus

Geometric analysis of Kemeny aggregation

Geometric interpretation and proof of the main result

Numerical experiments

Conclusion

Conclusion

We have established a theoretical result that allows to control the Kendall's tau distance between a permutation and the Kemeny consensuses of any dataset.

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

Conclusion

- We have established a theoretical result that allows to control the Kendall's tau distance between a permutation and the Kemeny consensuses of any dataset.
- This provides a simple and general method to predict, for any ranking aggregation procedure, how close the outcome on a dataset is from the Kemeny consensuses.

Future directions

The geometric properties of the Kemeny embedding are rich and could lead to many more results.

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 の�?

Future directions

The geometric properties of the Kemeny embedding are rich and could lead to many more results.

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

 We can imagine ranking aggregation procedures using a smaller scope for Kemeny consensuses.

Future directions

The geometric properties of the Kemeny embedding are rich and could lead to many more results.

- We can imagine ranking aggregation procedures using a smaller scope for Kemeny consensuses.
- Possible extensions to incomplete rankings.

Thank you