



# A Constrained Distance-Based Approach to Social Choice

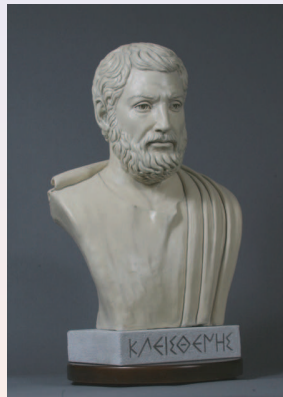
Farzad Farnoud (Hassanzadeh)

with O. Milenkovic

10/15/12

# Democracy: Greece, 2600 years ago

- Solon and Cleisthenis created the modern voting system.
- Black and white stones used to express preferences between candidates  $a$  and  $b$ :  $(a, b)$ ,  $(b, a)$ .
- Winner declared based on simple plurality count.



# Democracy: France, de Borda, 1784

- Simple plurality is “unquestionable” only for competitions between two candidates.
- Plurality voting versus pairwise majority rules

1	7	7	6	plur.	pmv
a	a	b	c	a	c
b	c	c	b	b	b
c	b	a	a	c	a



# Democracy: France, de Borda, 1784

- **Simple plurality** is “unquestionable” only for competitions between two candidates.
- **Borda's scoring method** [1784]:
  - each voter ranks all candidates instead of voting for one;
  - score of vote equal to rank;
  - small total scores preferred;

a	b	a	d	a (8=1+2+1+4)
b	a	c	c	b (10=2+1+4+3)
d	c	d	b	c (11=4+3+2+2)
c	d	b	a	d (11=3+4+3+1)



## Essay on the Application of Analysis to the Probability of Majority Decisions [1785]

**Condorcet's paradox:** Majority preferences may be intransitive with more than two options: majority prefers **a** to **b**, **b** to **c**, and **c** to **a**.

**Example:** three votes  
 $(a, b, c), (b, c, a), (c, a, b)$



## Essay on the Application of Analysis to the Probability of Majority Decisions [1785]

Condorcet's jury theorem: two options to vote for, one of which is correct. Each voter has probability  $p$  of correct vote. How many independent voters are needed for correct decision via majority voting?

- $p > 1/2$ , "the more the merrier".
- $p < 1/2$ , best jury consists of one voter only.



# Democracy: USA, Arrow, 1950's

- Arrow's impossibility theorem:  
Democracy is not possible!
- Axioms for Nobel prize:
  - No dictator
  - The preference ordering between two candidates **does not depend** on other candidates.
  - If **all voters** prefer A to B, the aggregate has to prefer A to B.
- No aggregate satisfies axioms!



# It's not just political sciences

We often encounter rankings of:

- politicians, celebrities, performers, job candidates
- schools, teams in professional sports
- movies, products
- emotions, eligibility for marriage etc.

Ranking relevant in many CS/ENG applications

- Computer science (search engines, etc)
- Recommender systems, marketing
- Social sciences: competitions, voting
- Management and decision making












# Rank aggregation

**Rank Aggregation:** Combining a set of rankings such that the result is a ranking “representative” of the set

Expert 1	Expert 2	Expert 3	Aggregate
GTech	UIUC	UCB	?
UIUC	UCB	UIUC	?
Stanford	GTech	MIT	?
MIT	MIT	Stanford	?
UCB	Standford	Gtech	?

# Rank aggregation

Expert 1	Expert 2	Expert 3	Aggregate
			?
			?
			?

# Rankings (permutations)

Mathematically, rankings are abstracted as permutations

Permutations are **arrangements** of a set of objects.

Example: **(b, c, a)** – a permutation over the set  $\{a, b, c\}$

One common approach to rank aggregation is “**distance-based**” rank aggregation.

Given expert rankings  $\sigma_1, \sigma_2, \dots, \sigma_m$ , the rank aggregation problem can be stated as

$$\pi^* = \arg \min_{\pi} \sum_{i=1}^m d(\pi, \sigma_i).$$

Rank aggregation requires a **distance function** over the space of permutations

- Kemeny 59 Kemeny's axiomatic approach to determine appropriate distance function, use of Kendall's  $\tau$
- Dwork 01 "Kemenization" is NP-hard, bipartite matching and Markov chain methods for aggregation, by Dwork et al.
- Sculley 07 Aggregation with similarity score, by Sculley
- Kumar 10 Generalizing Kendall's  $\tau$  and Spearman's footrule, by Kumar et al.

# Kemeny's axioms

Kemeny's axiomatic approach for determining a distance function:

- ❶  $d(\cdot, \cdot)$  is a metric
- ❷ Relabeling of objects does not change distance
- ❸  $d(\sigma, \pi) = d(\pi, \omega) + d(\omega, \sigma)$  iff  $\omega$  is “between”  $\pi$  and  $\sigma$ .  
Betweenness: for  $a, b \in [n]$ , if  $\pi$  and  $\sigma$  both rank  $a$  before  $b$ , then  $\omega$  also ranks  $a$  before  $b$
- ❹ If two rankings agree except on a “segment,” position of segment within ranking is not important:  
 $d(abcd e, abdce) = d(cdabe, dcabe)$ .



# Kendall's $\tau$

The unique distance that satisfies Kemeny's axioms is Kendall's  $\tau$

Kendall's  $\tau$ : minimum number of swaps of adjacent elements needed to transform one into the other

A swap of two elements is called a transposition

Transposition of elements in positions  $i$  and  $j$  is denoted by  $(ij)$

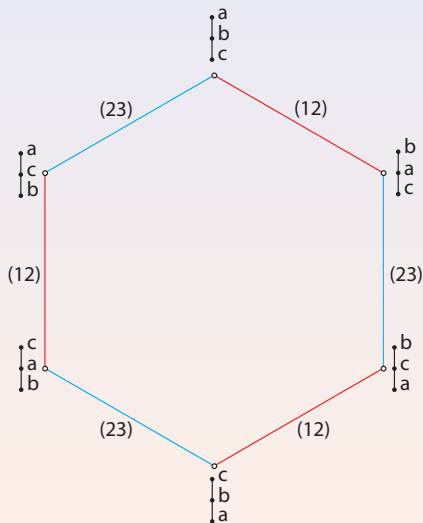
Example:  $d(abcde, cabde) = 2$  :  $abcde \xrightarrow{(23)} acbde \xrightarrow{(12)} cabde$

# Kendall's $\tau$

Kendall's  $\tau$  can be represented by a graph with  $n!$  vertices.

Neighboring vertices differ by an adjacent transposition

Distance is the length of the shortest path



# Rank aggregation: need for new distances

Need a new distance function that addresses shortcomings of Kendall's  $\tau$  in terms of having following additional properties:

- 1 Top versus bottom

$$d(\textcolor{red}{a}bcd, \textcolor{red}{b}acd) > d(abcd, ab\textcolor{red}{d}c)$$

- 2 Similar items versus dissimilar items

$$d(\textcolor{red}{a}b'ba', \textcolor{red}{b}'aba') > d(\textcolor{red}{a}a'bb', \textcolor{red}{a}'abb')$$

Ease of calculation or approximation required!



# Generalizing Kendall's distance

How should the axioms be changed?

- Let us **remove the fourth axiom**

- ① Distance function is a pseudo-metric
- ② Relabeling of objects does not change distance.
- ③  $d(\sigma, \pi) = d(\pi, \omega) + d(\omega, \sigma)$  iff  $\omega$  is between  $\pi$  and  $\sigma$
- ④ ~~If two rankings agree except on a "segment," position of segment within ranking is not important:  
 $d(ab\textcolor{red}{cd}e, ab\textcolor{red}{dce}) = d(\textcolor{red}{cd}abe, \textcolor{red}{dc}abe)$ .~~

# Generalizing Kendall's distance

How should the axioms be changed?

- Let us **remove the fourth axiom**

- ① Distance function is a pseudo-metric
- ② Relabeling of objects does not change distance.
- ③  $d(\sigma, \pi) = d(\pi, \omega) + d(\omega, \sigma)$  iff  $\omega$  is between  $\pi$  and  $\sigma$
- ④ ~~If two rankings agree except on a “segment,” position of segment within ranking is not important:  
 $d(\text{ab}\text{cd}\text{e}, \text{ab}\text{dce}) = d(\text{cd}\text{abe}, \text{dcabe})$ .~~

The solution is again **Kendall  $\tau$ !!**

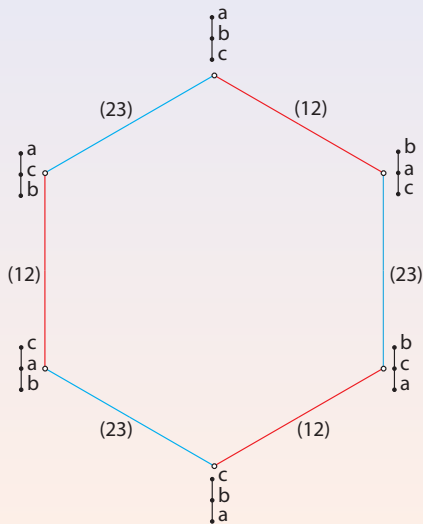
Removing the fourth axiom is **not sufficient**. Also need to modify the third axiom

# Why modify the third axiom?

Lemma [F, Touri, Milenkovic]:  
For complete rankings, **fourth axiom** follows from **third axiom**.

Special case:  $n = 3$

Consider the distinct paths  
between  $(a, b, c)$  and  $(c, b, a)$ .



# Generalizing Kendall's distance

Our relaxation of Kemeny's axioms:

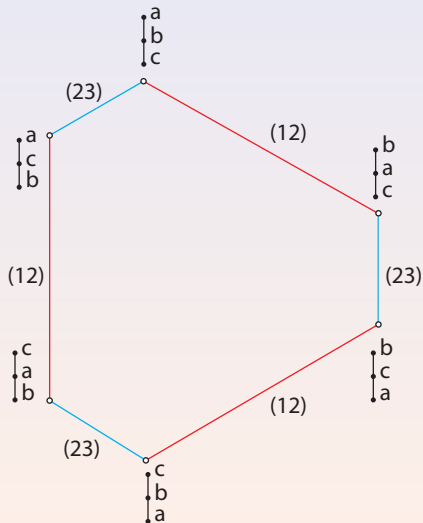
- 1 Distance function is a pseudo-metric
- 2 Relabeling of objects does not change distance.
- 3  $d(\sigma, \pi) = d(\pi, \omega) + d(\omega, \sigma)$  iff  $\omega$  is "between"  $\pi$  and  $\sigma$  for some  $\omega$  between  $\pi$  and  $\sigma$  and distinct from them if  $\pi$  and  $\sigma$  disagree on more than one pair of elements.
- 4 ~~If two rankings agree except on a "segment," position of segment within ranking is not important:~~  
 ~~$d(abcd e, abdc e) = d(cdabe, dcabe)$ .~~

Unique solution: weighted (cost constrained) Kendall's  $\tau$ ! [F, Touri, Milenkovic, 2012]

# New Distance: weighted Kendall distance

**Weighted Kendall distance:**  
minimum cost of transforming  
one permutation into the other  
using **adjacent transpositions**  
where each adjacent  
transposition has a given **cost**

Cost of transposition  $(ij)$  is  
denoted by  $\varphi(i, j)$



# Computing distance

Computing Kendall's  $\tau$  is straightforward: count the number of out of order pairs.

How to compute the weighted Kendall distance for general cost function is not known, but is known for a very important case.

**Monotonic cost function:**  $\varphi$  is monotonic if  $\varphi(i, i+1)$  is monotonic in  $i$ .

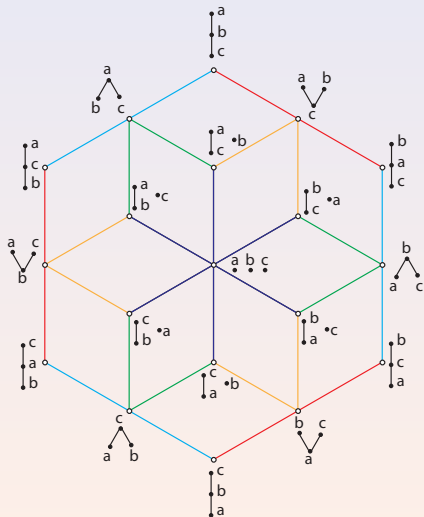
**Theorem** [F, Touri, Milenkovic]: Weighted Kendall distance with monotonic cost can be computed in time  $O(n^4)$ .

**Theorem** [F, Milenkovic]: 2-approximation for weighted Kendall distance with general cost can be computed in time  $O(n^2)$ .

# Partial rankings and partially ordered sets

Bogart [1973] generalizes  
Kemeny's approach to **partially  
ordered sets**.

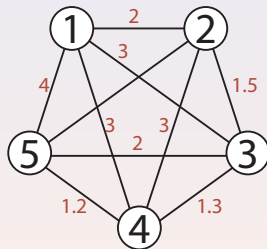
Our relaxation also generalizes  
to partially ordered sets (work  
in progress)



# New Distance: weighted transposition distance

We assign cost  $\varphi(i, j) \geq 0$  to  
any transposition  $(ij)$ ,  
 $\varphi$  is called a **cost function**

**Weighted transposition distance:**  
between two permutations  
 $\pi$  and  $\sigma$  is the **minimum**  
**cost of transforming  $\pi$  into  $\sigma$**   
using transpositions =  $d_\varphi(\pi, \sigma)$

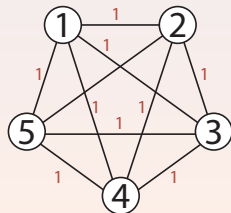




# Rank aggregation: common distance functions

Several distance functions used for rank aggregation [Diaconis and Graham 88]:

- **Kendall's  $\tau$ :**  $K(\pi, \sigma) = \#$  of transpositions of adjacent ranks.  
Equivalent to  $\varphi_K(i, i+1) = 1$ .
- **Spearman's Footrule:**  $F(\pi, \sigma) = \sum_i |\pi(i) - \sigma(i)|$ . Equivalent to the path cost function  $\varphi_F(i, j) = |i - j|$ .
- **Cayley's distance:**  
 $T(\pi, \sigma) = \#$  of transpositions  
Equivalent to  $\varphi_T(i, j) = 1$ .



# Three stage algorithm for computing distance

- ① Distance of a **single transposition** from identity: e.g.  $d(12345, 42315)$ 
  - A **Viterbi-style** algorithm on a trellis, or
  - **Bellman-Ford** type algorithm over graphs
- ② Distance of a **single cycle** from identity
  - A **dynamic program** finds an approximation,
  - Proof of approximation using “**h-transpositions**”
- ③ Distance of a **general permutation** from identity
  - By extending results for single cycle permutations

---

See F.Farnoud and O.Milenkovic, Sorting of permutations by weighted transpositions. IT Transaction, 58(1):3–23, Jan. 2012.

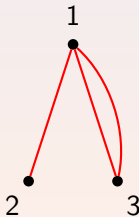
# Transformations and multigraphs

A **sequence of transpositions** that transforms one permutation to another is called a **transformation**.

A transformation can be **represented by a multigraph**

The **vertices** of the multigraph are  $\{1, \dots, n\}$ , while the **edges** are the **transpositions** of the transformation.

Example: Transformation  $(13), (12), (13)$  transforms  $\pi = (a, c, b)$  into  $e = (a, b, c)$



# Computing distance: transpositions

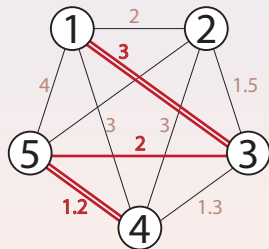
**Theorem:** For  $i, j \in [n]$ , let  $\tau$  be the minimum cost transformation of  $\pi = (ij)$  to identity. The multigraph of  $\tau$  is of the form

$2 \times (\text{a path between } i \text{ and } j) - (\text{one edge}).$

Example: Transformation of  $\pi = 42315$

**Theorem:** Distance between a permutation  $\pi = (ij)$  and identity can be computed in time  $O(n^4)$ .

A modification of the [Bellman-Ford](#) shortest path algorithm can be used.



# Computing distance

- **Constant approximation algorithm** (const=4) for arbitrary cost functions  $\varphi$  in  $O(n^4)$  operations
- **Constant approximation algorithm** (const=2), if cost function  $\varphi$  is a metric, in  $O(n^4)$  operations
- **Constant approximation algorithm** (const=2) for path cost functions (e.g. **weighted Kendall**) in  $O(n^4)$  operations
- **Exact algorithms** for metric-path cost functions (e.g. **weighted Spearman's Footrule**) in  $O(n^2)$  operations.

---

See F.Farnoud and O.Milenkovic, Sorting of permutations by weighted transpositions. IT Transaction, 58(1):3–23, Jan. 2012.

# Rank aggregation

- **Weighted Kendall distance** generalizes Kendall's  $\tau$  to model the significance of **top vs bottom** of a ranking, e.g.,

$$\varphi(1, 2) > \varphi(9, 10)$$

- **Weighted transposition distance** generalizes Cayley's distance to model **similarities and dissimilarities** of elements, e.g.,

$$\begin{aligned}\varphi(\text{Godfather I}, \text{Godfather II}) \\ &< \varphi(\text{Godfather I}, \text{Goodfellas}) \\ &< \varphi(\text{Godfather I}, \text{Star Wars})\end{aligned}$$

# Rank aggregation

Recall: given voter rankings  $\sigma_1, \sigma_2, \dots, \sigma_m$ , rank aggregation solves

$$\pi^* = \arg \min_{\pi} \sum_{i=1}^m d_{\varphi}(\pi, \sigma_i).$$

For many distance functions, problem is **NP-hard**.

Alternative ways to find reasonable solutions

- **Approximation**: 2-approximation or 4-approximation (depending on type of  $\varphi$ )
- Using Matching algorithms and finding **local optimum** instead of global optimum
- **Markov chain**[Dwork et al. 01] methods

# Rank aggregation: approximation

For general cost function  $\varphi$ , to find

$$\pi^* = \arg \min_{\pi} \sum_{i=1}^m d_{\varphi}(\pi, \sigma_i)$$

we approximate  $d_{\varphi}$  by  $D$  such that

$$(1/2)D(\pi, \sigma) \leq d_{\varphi}(\pi, \sigma) \leq 2D(\pi, \sigma).$$

We can find

$$\pi' = \arg \min_{\pi} \sum_{i=1}^m D(\pi, \sigma_i)$$

and can show that

$$\sum_{i=1}^m d_{\varphi}(\pi', \sigma_i) \leq 4 \sum_{i=1}^m d_{\varphi}(\pi^*, \sigma_i).$$



# Rank aggregation

Students were asked to rank the following items in order of importance in their academic life:

- 1 Campus friendliness and inclusiveness
- 2 Availability of recreational and cultural facilities
- 3 Quality of classrooms and dorms
- 4 Extracurricular student groups and activities
- 5 Geographical proximity to your family/boyfriend/girlfriend
- 6 Commitment of campus to build a diverse community
- 7 Being able to express one's personal identity freely
- 8 Being able to make friends on campus
- 9 Safety and security
- 10 Availability of financial support/scholarship
- 11 Availability of personal counseling/academic tutoring
- 12 Friendliness/academic prowess of faculty members/instructors

We used the cost function  $\varphi(i, i + 1) = (3/4)^{i-1}$ .

# Rank aggregation

	Aggregate Ranking
Graduate (28)	10, 12, 9, 8, 1, 3, 2, 11, 7, 5, 4, 6
Undergrad (73)	12, 9, 8, 1, 3, 10, 4, 2, 11, 7, 5, 6

- 1 Campus friendliness and inclusiveness
- 2 Availability of recreational and cultural facilities
- 3 Quality of classrooms and dorms
- 4 Extracurricular student groups and activities
- 5 Geographical proximity to your family/boyfriend/girlfriend
- 6 Commitment of campus to build a diverse community
- 7 Being able to express one's personal identity freely
- 8 Being able to make friends on campus
- 9 Safety and security
- 10 Availability of financial support/scholarship
- 11 Availability of personal counseling/academic tutoring
- 12 Friendliness/academic prowess of faculty members/instructors

# Rank aggregation

	Aggregate Ranking
Undergrad/Female (32)	12, 9, 1, 8, 3, 4, 2, 5, 10, 11, 7, 6
Undergrad/Male (31)	12, 9, 3, 1, 8, 10, 4, 2, 11, 7, 5, 6
Undergrad/? (10)	8, 12, 4, 1, 3, 9, 7, 2, 10, 11, 6, 5

- 1 Campus friendliness and inclusiveness
- 2 Availability of recreational and cultural facilities
- 3 Quality of classrooms and dorms
- 4 Extracurricular student groups and activities
- 5 Geographical proximity to your family/boyfriend/girlfriend
- 6 Commitment of campus to build a diverse community
- 7 Being able to express one's personal identity freely
- 8 Being able to make friends on campus
- 9 Safety and security
- 10 Availability of financial support/scholarship
- 11 Availability of personal counseling/academic tutoring
- 12 Friendliness/academic prowess of faculty members/instructors

# Distributed rank aggregation

## Borda's aggregation over networks:

Network modeled by a **connected** graph  $G = ([m], E)$ .

Voters are vertices and edges indicate connectivity.

$b_i(t)$  is the vector of Borda scores according to voter  $i$  at time  $t$ .

- 1 At time  $t \geq 0$ , pick an edge  $\{i, i'\} \in E$  with **probability**  $P_{ii'} > 0$ , where  $\sum_{\{i, i'\} \in E} P_{ii'} = 1$ ,
- 2  $i, i'$  **exchange** their estimate  $b_i(t), b_{i'}(t)$  and they let  $b_i(t+1) = b_{i'}(t+1) = \frac{1}{2}(b_i(t) + b_{i'}(t))$ ,
- 3 voters  $\ell \neq i, i'$  let  $b_\ell(t+1) = b_\ell(t)$ .

**Well-known:** Almost surely  $\lim_{t \rightarrow \infty} b_i(t) = \bar{b}$  where  $\bar{b} = \frac{1}{m} \sum_{i=1}^m \bar{b}_i(0)$  [Boyd et al.].

# Distributed rank aggregation

**Definition:**  $t$  is a **consensus time** if the ordering of  $b_i(t)$  matches ordering of  $\bar{b}$ , for all  $i \in [m]$ .

$$T = \min\{t \geq 0 \mid t \text{ is a consensus time for the ordering.}\}$$

$r^j = \min(\bar{b}^{j+1} - \bar{b}^j, \bar{b}^j - \bar{b}^{j-1})$  : **minimum distance of average rating of  $j$  from neighboring candidates.**

$d^j = \max_i b_i^j(0) - \min_i b_i^j(0)$  : **spread of the initial ratings of the object  $j$  among voters.**

$$P(T > t) \leq 4m\lambda_2^t(W) \sum_{j=1}^n \left(\frac{d^j}{r^j}\right)^2,$$

$W = \sum_{\{i,j\} \in E} P_{ij}(I - \frac{1}{2}(e_i - e_j)(e_i - e_j)^T)$ ,  $\lambda_2(W)$  = **second largest eigenvalue** of  $W$ .

Thank you!