

# L15 Positional scored based voting rules

CS 295 Introduction to Algorithmic Game Theory  
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Based on works of Ariel Procaccia

# Recap

**Theorem (Gibbard-Satterthwaite).** *Let  $f$  be a monotone social choice function onto  $A$  with  $|A| \geq 3$ , then  $f$  is a *dictatorship*.*

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Example:

Choose a voter at **random** and ask him/her to **vote**. How to we “**measure**” the performance of the mechanism? What are the guarantees?

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Choose a voter at **random** and ask him/her to **vote**. How to we “**measure**” the performance of the mechanism? What are the guarantees?

Answer: Positional scoring-based rules.

# Positional scoring-based rules

**Definition (Positional score based rule).** Let  $n$  be the number of voters and  $m$  the number of candidates. Each voter  $i$  has preference  $>_i$ . A positional scoring rule is defined by a vector of nonnegative real numbers  $a = (a_1, \dots, a_n)$  so that the score of candidate  $x$  is given by

$$sc(x, >) = \sum_{i=1}^n a_{>_i(x)}.$$

Examples:

- **Plurality:**  $a = (1, 0, \dots, 0)$ .
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**Goal:** Design positional scoring rules that are incentive compatible and close to deterministic score-based rules (winner is the candidate with **maximum score**).

# First approach

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Rule 1: Select a voter  $i$  uniformly at random. Elect the **winner  $x$**  according to the following **probability distribution**

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**Theorem (General Guarantee).** *Let  $f$  be a positional scoring rule with parameters  $a$ . Then the approximation ratio of Rule 1 with respect to  $f$  is  $\Omega\left(\frac{1}{\sqrt{m}}\right)$ .*

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*Proof.* Assume  $>$  is a preference profile and  $a$  is the candidate with the **maximum score**, i.e.,

$$sc(a, >) = \text{OPT}.$$

Let SUM be the total score of all candidates, that is

$$\text{SUM} = \sum_{x \in A} sc(x, >) = n \sum_{j=1}^m a_j.$$

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*Proof cont.*

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Rule 1 chooses candidate  $x$  with probability

$$\sum_{i \in I} \Pr[\text{choose voter } i] \times \Pr[i \text{ chooses } x] = \frac{1}{n} \sum_{i \in I} \frac{a_{>_i(x)}}{\sum_{j=1}^n a_j}$$

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Hence, the expected score of the winner is

$$\frac{sc(a, >)}{\text{SUM}} \cdot \text{OPT} + \sum_{x \neq a, x \in A} \frac{sc(x, >)}{\text{SUM}} \cdot sc(x, >).$$

We need to lower bound the above.

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Recall CS inequality that is

$$\left( \sum_j b_j^2 \right) \left( \sum_j c_j^2 \right) \geq \left( \sum_j b_j c_j \right)^2 \quad \text{hence}$$



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Finally observe that

$$\text{SUM} - \text{OPT} = \sum_{x \neq a, x \in A} sc(x, >).$$

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Therefore we conclude

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The function  $f(x) = \frac{\frac{x}{\text{SUM}} \cdot x + \frac{1}{m-1} \frac{(\text{SUM} - x)^2}{\text{SUM}}}{x}$  is minimized for  $x = \frac{\text{SUM}}{\sqrt{m}}$  and this gives  $\approx \frac{2}{\sqrt{m}}$  approximation ratio.

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**The winner will get expected score  $\Omega\left(\frac{1}{\sqrt{m}}\right) \times \text{OPT}$**

# Further Approximations

**Borda:**  $a = (m - 1, m - 2, \dots, 0)$ .

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*Proof.* If we assume Borda voting rule, we can get better approximation. Recall

$$sc(a, >) = \text{OPT}.$$

$$\text{SUM} = \sum_{x \in A} sc(x, >) = n \sum_{j=1}^m a_j.$$

The winner gets expected score **at least**

$$\frac{\text{OPT}}{\text{SUM}} \cdot \text{OPT} + \frac{1}{m-1} \frac{(\text{SUM} - \text{OPT})^2}{\text{SUM}}$$

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The **winner gets expected score at least**

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The idea is that  $\text{SUM} = \frac{nm(m-1)}{2}$  and  $\text{OPT} \leq n(m-1)$ .



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with

$$\frac{OPT}{SUM} \leq \frac{2}{m} \text{ so we can improve the previous analysis!}$$

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The function  $f(x) = \frac{\frac{x}{\text{SUM}} \cdot x + \frac{1}{m-1} \frac{(\text{SUM} - x)^2}{\text{SUM}}}{x}$  subject to  $x \leq \frac{2\text{SUM}}{m}$  is minimized for  $x = \frac{2\text{SUM}}{m}$  and this gives  $\frac{1}{2} + \Omega\left(\frac{1}{m}\right)$  approximation ratio.

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**Veto:**  $a = (1, 1, \dots, 1, 0)$ .

**Theorem (Veto Guarantee).** *Rule 1 gives a  $1 - O\left(\frac{1}{m}\right)$ -approximation with respect to Veto.*

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# Lower bounds

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Remark:

- Rule 1 is **tight for Plurality!**
- The proof uses **Yao's min-max principle:**

**Best randomized algorithm over worst deterministic input**  
**same guarantees as worst distribution input of best**  
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Remark:

- Rule 1 is **not** tight for Plurality!
- The proof uses Yao's min-max principle.

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Rule 2: Choose a **pair of alternatives** uniformly at **random**. If one is preferred to the other by a **majority** of agents then it is the **winner**. Break ties at random.

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- **Other** **Duple := voting rule of range at most 2.**

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