

Ranking in rounds, with application to matchmaking

Hafedh El Ferchichi, Matthieu Lerasle, Vianney Perchet

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INSTITUT
POLYTECHNIQUE
DE PARIS



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- Design a matchmaking system for 1vs1 games or sport (like Elo for chess or TrueSkill for videogames).
- At each iteration: **Every player must be matched.**
- $\{i, j\}$ is a good match if

$$|\mathbb{P}(i \text{ defeats } j) - \frac{1}{2}| \leq \varepsilon^* \quad (1)$$

where $\varepsilon^* > 0$ is chosen by an operator.

Problem formulation

- $\varepsilon_{i,j} = \mathbb{P}(i \text{ defeats } j) - \frac{1}{2}$ the "Skill Gap"
- Choose M_t a maximal matching such that: if $\{i,j\} \in M_t$ then players i and j play against each other.
- The **cost** of a matching M :

$$C_M = \sum_{\{i,j\} \in M} \mathbb{1}_{|\varepsilon_{i,j}| > \varepsilon^*} \quad (2)$$

- The regret is:

$$C_M - C_{M^*} \quad (3)$$

where $M^* \in \arg \min_{M \text{ matching}} C_M$

Main assumptions

Assumption 1 (Strong Stochastic Transitivity SST)

If $\varepsilon_{i,j} \geq 0$ and $\varepsilon_{j,k} \geq 0$ then

$$\varepsilon_{i,k} \geq \max\{\varepsilon_{i,j}, \varepsilon_{j,k}\} \quad (4)$$

Assumption 2 (Stochastic Triangle inequality STI)

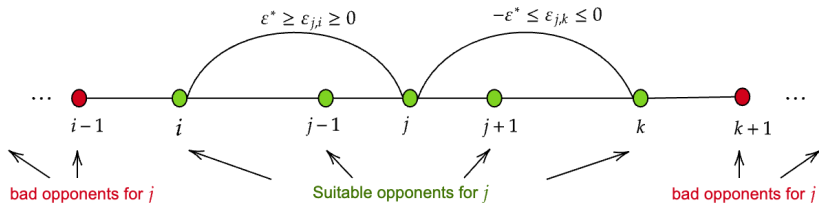
If $\varepsilon_{i,j} \geq 0$ and $\varepsilon_{j,k} \geq 0$ then

$$\varepsilon_{i,k} \leq \varepsilon_{i,j} + \varepsilon_{j,k} \quad (5)$$

Consequences of SST

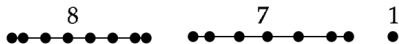
- **Unique ranking R :**

$$R(i) > R(j) \iff \varepsilon_{i,j} \geq 0 \quad (6)$$



The optimal matching costs:

$$C_{M^*} = \#\{\text{odd-sized connected components of affinity graph}\} \quad (7)$$



Definition 1 (ε -correct ranking)

a ranking \hat{R} is said to be ε -correct if

$$\hat{R}(i) > \hat{R}(j) \implies \varepsilon_{i,j} \geq -\varepsilon \quad (8)$$

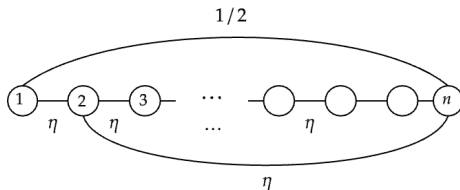
Definition 2 ((ε, δ) -PAC algorithm)

An algorithm that retrieve an ε -correct ranking with probability at least $1 - \delta$ is said to be (ε, δ) **Probably Approximately Correct (PAC)**

Without STI, there is an instance where any (ε, δ) -PAC algorithm requires $\Omega(n^2)$ comparisons (Falahatgar et al. [2017]).

Worst instance without (STI)

Consider an instance where $\varepsilon_{n,1} = 1/2$, and $|\varepsilon_{i,j}| = \eta$ when $\{i,j\} \neq \{1,n\}$.



- (ε, δ) -PAC: Sample complexity $\Omega\left(\frac{n}{\varepsilon^2} \log \frac{n}{\delta}\right)$ Falahatgar et al. [2017].
- Exact ranking requires Ren et al. [2019]

$$\Omega\left(\sum \frac{1}{\varepsilon_{i,i+1}^2} \left(\log \frac{n}{\delta} + \log \log \frac{1}{|\varepsilon_{i,i+1}|}\right)\right) \quad (9)$$

- Our method for (ε, δ) -PAC algorithm:
 - $O\left(\left(\frac{n}{\varepsilon^2} \log \frac{n}{\delta}\right) \log^3 n\right)$ Sample complexity.
 - $O\left(\left(\frac{1}{\varepsilon^2} \log \frac{n}{\delta}\right) \log^3 n\right)$ Time complexity
- Our method for exact ranking:
 - $O\left(\log^3 n \sum_i \frac{1}{\varepsilon_{i,i+1}^2} \left(\log\left(\frac{n}{\delta}\right) + \log \log \frac{1}{\varepsilon_{i,i+1}}\right)\right)$ Sample complexity.
 - $O\left(\frac{\log^3 n}{\min_i \varepsilon_{i,i+1}^2} \left(\log \frac{n}{\delta} + \log \log \frac{1}{\min_i |\varepsilon_{i,i+1}|}\right)\right)$ Time complexity.

- AKS sorting Network Ajtai et al. [1983]:
 - $O(\log n)$ matchings.
 - $O(n \log n)$ comparisons.
- COMPARE($i, j, \varepsilon, \delta$) substitutes for the comparators of AKS network:
Repeat a comparison to gain confidence

Lemma 1 (Theoretical Performance of COMPARE)

COMPARE terminates after $O(\varepsilon^{-2} \log(1/\delta))$ comparisons and returns the stronger player with probability at least $1/2$. Further, if $\varepsilon \leq |\varepsilon_{i,j}|$, then COMPARE returns the stronger player with probability at least $1 - \delta$. If "Confident" is returned, that implies that $\varepsilon_{i,j} \geq \varepsilon$ with probability at least $1 - \delta$

Theoretical Performance of $\text{AKS}(\varepsilon, \delta)$

Using COMPARE with parameter $\varepsilon' = \varepsilon/(2C^2 \log n)$ and $\delta' = \delta/(nC^2 \log^3 n)$ in AKS yield an (ε, δ) -PAC ranking algorithm.

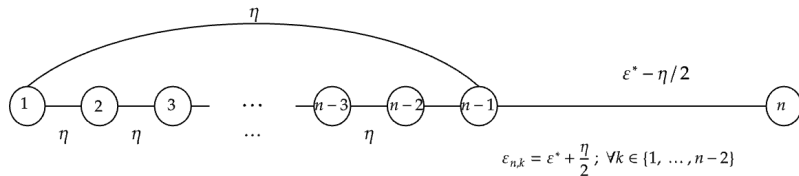
Theorem 1 (Performance of $\text{AKS}(\varepsilon, \delta)$)

$\text{AKS}(\varepsilon, \delta)$ uses at most $O(\varepsilon^{-2} n \log^3(n) \log(n/\delta))$ comparisons, and $O(\varepsilon^{-2} \log^3(n) \log(n/\delta))$ matchings.

Is (ε, δ) -PAC sufficient to retrieve an optimal matching?

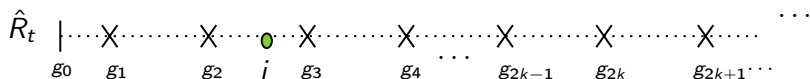
Unfortunately Not.

- Consider the following instance:



- Every ranking \hat{R} where $\hat{R}(\{1, \dots, n-1\}) < \hat{R}(n)$ is ε -correct.
- Need for $\frac{\eta}{2}$ -correct ranking (i.e. an exact ranking).

Exact Ranking Retrieval (ERR)



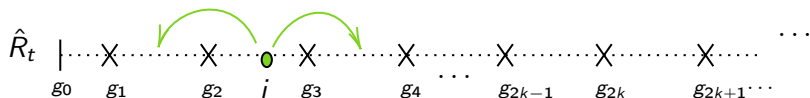
\hat{R}_t is ε -correct

$$\varepsilon_{g_{i+1}, g_i} > \varepsilon$$

\times : Frontiers

\dots : Cross at most one frontier

Exact Ranking Retrieval (ERR)



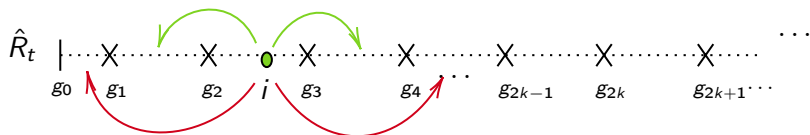
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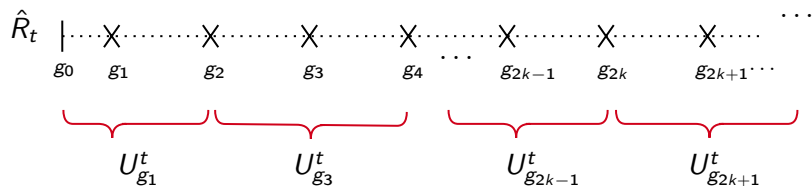
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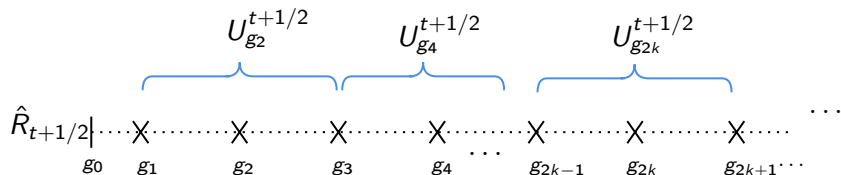
\hat{R}_t is ε -correct

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Exact Ranking Retrieval (ERR)



\hat{R}_t is ε -correct

$\varepsilon_{g_{i+1}, g_i} > \varepsilon$

\times : Frontiers

\dots : Cross at most one frontier

- Players that reached their true ranking are recognizable.
- These players don't have to participate in ranking anymore (moves to gap estimation right away).
- Performance: Let $\Delta_i = \min\{|\varepsilon_{i,i+1}|, |\varepsilon_{i,i-1}|\}$
 - Sample complexity:

$$O\left(\log^3 n \sum_i \frac{1}{\Delta_i^2} (\log(n/\delta) + \log \log \frac{1}{\Delta_i})\right) \quad (10)$$

- Time complexity(for player i):

$$O\left(\frac{\log^3 n}{\Delta_i^2} (\log \frac{n}{\delta} + \log \log \frac{1}{\Delta_i})\right) \quad (11)$$

Neighboring gap estimation

For this Phase: the exact ranking is provided.

$$\begin{array}{ccc} \varepsilon_{i,i-1} = \varepsilon^* - \eta & & \\ \circ & \text{---} & \circ & & \circ \\ i-1 & & i & & i+1 \\ & & & & \varepsilon_{i+1,i} = \varepsilon^* + \eta \end{array}$$

- Costs $O\left(\frac{1}{\eta^2} \log\left(\frac{1}{\delta}\right)\right)$
- if $\eta_{i,i+1} = |\varepsilon^* - |\varepsilon_{i,i+1}||$, we have:
 - Sample complexity of retrieving an optimal matching is:

$$O\left(\sum_i \frac{1}{\eta_{i,i+1}^2} (\log(n/\delta) + \log \log \frac{1}{\eta_{i,i+1}})\right) \quad (12)$$

- A cost of:

$$O\left(\sum_{i: |\varepsilon_{i,i+1}| > \varepsilon^*} \frac{1}{\eta_{i,i+1}^2} (\log(n/\delta) + \log \log \frac{1}{\eta_{i,i+1}})\right) \quad (13)$$

- (ε, δ) -PAC ranking:
 - Time complexity: $O\left(\frac{\log^3 n}{\varepsilon^2} \log(n/\delta)\right)$
- Exact Ranking Retrieval:
 - Time complexity (for player i): $O\left(\frac{\log^3 n}{\Delta_i^2} (\log(\frac{n}{\delta}) + \log \log \frac{1}{\Delta_i})\right)$
 - Cost for player i : $O\left(\frac{\log^3 n}{\Delta_i^2} (\log(\frac{n}{\delta}) + \log \log \frac{1}{\Delta_i})\right)$
- Gap estimation:
 - Time complexity: $O\left(\frac{1}{\min_i \eta_i^2} (\log(\frac{n}{\delta}) + \log \log \frac{1}{\min_i \eta_i^2})\right)$
 - Cost: $O\left(\sum_{|\varepsilon_{i,i+1}| > \varepsilon^*} \frac{1}{\eta_{i,i+1}^2} (\log(n/\delta) + \log \log \frac{1}{\eta_{i,i+1}})\right)$

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- Moein Falahatgar, Yi Hao, Alon Orlitsky, Venkatadheeraj Pichapati, and Vaishakh Ravindrakumar. Maxing and ranking with few assumptions. *Advances in Neural Information Processing Systems*, 30, 2017.
- Wenbo Ren, Jia (Kevin) Liu, and Ness Shroff. On sample complexity upper and lower bounds for exact ranking from noisy comparisons. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

Questions ?