

Rankings and Tournaments: A new approach

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(joint with Miguel Brozos-Vázquez, Marco Antonio Campo-Cabana, and José Carlos Díaz-Ramos)



Outline

- 1 Motivation
- 2 The model
- 3 Ranking Methods
- 4 Our contribution

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Rank the participants in a tournament

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- Ranking candidates in labor markets

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- Characterized axiomatically by Palacios-Huerta and Volij (2004)

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- Many ties
- Only makes sense for Round-Robin tournaments (because of IIA).

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Invariant method: $r_i^\infty := \sum_j \frac{a_{ij}}{\sum_k a_{kj}} r_j^\infty$

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- Quasi-flatness preservation
- Negative responsiveness to losses

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- Asymmetric treatment of victories with respect to losses (because of negative responsiveness to losses)
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The ranking proposed for A is the inverse of the one proposed for A^t

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$$F(r_i - r_j) = \frac{e^{r_i}}{e^{r_i} + e^{r_j}}$$

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Paired comparison analysis (Statistics)

Completely different approach

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- In chess tournaments also a logistic distribution has proved to fit the observed data quite well

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- What about non-asymptotic behavior?

Outline

- 1 Motivation
- 2 The model
- 3 Ranking Methods
- 4 Our contribution

Idea

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Fair-Bets: The iterative method (linear system) to use all the information of the tournament

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Maximum-Likelihood: The problems derived from the non-linearity of the system to be solved (lack of robustness on F , computation costs)

Recursive Performance

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$r_i^1 =$ “performance of i ”

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- Symmetric treatment of victories and losses. The ranking proposed for A is the inverse of the ranking proposed by A^t
- The proposed rating is robust in F
- According to the proposed rating, the performance of each player coincides with his own rating

Round Robin

When restricting attention to round robin tournaments we get:

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Scores = Maximum Likelihood = Recursive Performance \neq Fair Bets

Some numeric examples

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A_1				$(av. scores)$ s	RP	ML	FB
0	1	0.9	0.9	0.7	1.010	1.099	0.703
1	0	0.9	0	0.633	1.037	1.099	0.703
0.1	0.1	0	0	0.1	-1.017	-1.099	0.078
0.1	0	0	0	0.1	-1.031	-1.099	0.078

Some numeric examples

				$(av. scores)$	RP	ML	FB
				s			
A_1							
$\begin{pmatrix} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{pmatrix}$	0	1	0.9	0.7	1.010	1.099	0.703
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				$(av. scores)$	RP	ML	FB
				s			
A_2							
$\begin{pmatrix} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{pmatrix}$	0	1	90	0.892	1.127	1.099	0.703
	1	0	0.9	0.633	0.971	1.099	0.703
	10	0.1	0	0.1	-1.049	-1.099	0.078
	0.1	0	0	0.1	-1.048	-1.099	0.078

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	A_1	$(av. scores)$ s	RP	ML	FB
$\left(\begin{array}{cccc} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$		0.7	1.010	1.099	0.703
		0.633	1.037	1.099	0.703
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	A_2	$(av. scores)$ s	RP	ML	FB
$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$		0.892	1.127	1.099	0.703
		0.633	0.971	1.099	0.703
		0.1	-1.049	-1.099	0.078
		0.1	-1.048	-1.099	0.078

	A_3	$(av. scores)$ s	RP	ML	FB
$\left(\begin{array}{cccc} 0 & 0.9 & 90 & 0.9 \\ 1.1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$		0.891	1.087	1.055	0.637
		0.667	1.082	1.227	0.764
		0.1	-1.085	-1.140	0.071
		0.1	-1.084	-1.142	0.070

Directions for future research

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- Axiomatic analysis of the recursive performance ranking method

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- Develop comparative studies of the different ranking methods in applied settings

Rankings and Tournaments: A new approach

Julio González-Díaz

Kellogg School of Management (CMS-EMS)
Northwestern University
and
Research Group in Economic Analysis
Universidad de Vigo

.....

(joint with Miguel Brozos-Vázquez, Marco Antonio Campo-Cabana, and José Carlos Díaz-Ramos)



Some tournaments

[Return](#)

Some tournaments

A_2				<i>(av. scores)</i>			
				s	++	++	++
$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$				0.892	---	---	---
				0.633	---	---	---
				0.1	---	---	---
				0.1	---	---	---

Some tournaments

A_1				(av.scores)				
				s	++	++	++	
$\left(\begin{array}{cccc} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.7	----	----	----
					0.633	----	----	----
					0.1	----	----	----
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$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.892	----	----	----
					0.633	----	----	----
					0.1	----	----	----
					0.1	----	----	----

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$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.892	----	----	----
					0.633	----	----	----
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A_3				(av. scores)				
				s	++	++	++	
$\left(\begin{array}{cccc} 0 & 0.9 & 90 & 0.9 \\ 1.1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.891	----	----	----
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					0.667	----	----	----
					0.1	----	----	----
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					0.633	----	----	----
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$\left(\begin{array}{cccc} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.7	1.010	1.099	0.703
					0.633	1.037	1.099	0.703
					0.1	-1.017	-1.099	0.078
					0.1	-1.031	-1.099	0.078

A_2				(av. scores)				
				s	++	++	++	
$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.892	1.127	1.099	0.703
					0.633	0.971	1.099	0.703
					0.1	-1.049	-1.099	0.078
					0.1	-1.048	-1.099	0.078

A_3				(av. scores)				
				s	++	++	++	
$\left(\begin{array}{cccc} 0 & 0.9 & 90 & 0.9 \\ 1.1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$					0.891	1.087	1.055	0.637
					0.667	1.082	1.227	0.764
					0.1	-1.085	-1.140	0.071
					0.1	-1.084	-1.142	0.070

Some tournaments

A_1				<i>(av. scores)</i>			
				s	++	++	++
$\left(\begin{array}{cccc} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$				0.7	1.010	1.099	0.703
				0.633	1.037	1.099	0.703
				0.1	-1.017	-1.099	0.078
				0.1	-1.031	-1.099	0.078

A_2				<i>(av. scores)</i>			
				s	++	++	++
$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$				0.892	1.127	1.099	0.703
				0.633	0.971	1.099	0.703
				0.1	-1.049	-1.099	0.078
				0.1	-1.048	-1.099	0.078

A_3				<i>(av. scores)</i>			
				s	++	++	++
$\left(\begin{array}{cccc} 0 & 0.9 & 90 & 0.9 \\ 1.1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$				0.891	1.087	1.055	0.637
				0.667	1.082	1.227	0.764
				0.1	-1.085	-1.140	0.071
				0.1	-1.084	-1.142	0.070

Some tournaments

A_1				(<i>av.scores</i>) s	RP	ML	FB	
$\left(\begin{array}{cccc} 0 & 1 & 0.9 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$	0	1	0.9	0.9	0.7	1.010	1.099	0.703
	1	0	0.9	0	0.633	1.037	1.099	0.703
	0.1	0.1	0	0	0.1	-1.017	-1.099	0.078
	0.1	0	0	0	0.1	-1.031	-1.099	0.078

A_2				(<i>av.scores</i>) s	RP	ML	FB	
$\left(\begin{array}{cccc} 0 & 1 & 90 & 0.9 \\ 1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$	0	1	90	0.9	0.892	1.127	1.099	0.703
	1	0	0.9	0	0.633	0.971	1.099	0.703
	10	0.1	0	0	0.1	-1.049	-1.099	0.078
	0.1	0	0	0	0.1	-1.048	-1.099	0.078

A_3				(<i>av.scores</i>) s	RP	ML	FB	
$\left(\begin{array}{cccc} 0 & 0.9 & 90 & 0.9 \\ 1.1 & 0 & 0.9 & 0 \\ 10 & 0.1 & 0 & 0 \\ 0.1 & 0 & 0 & 0 \end{array} \right)$	0	0.9	90	0.9	0.891	1.087	1.055	0.637
	1.1	0	0.9	0	0.667	1.082	1.227	0.764
	10	0.1	0	0	0.1	-1.085	-1.140	0.071
	0.1	0	0	0	0.1	-1.084	-1.142	0.070