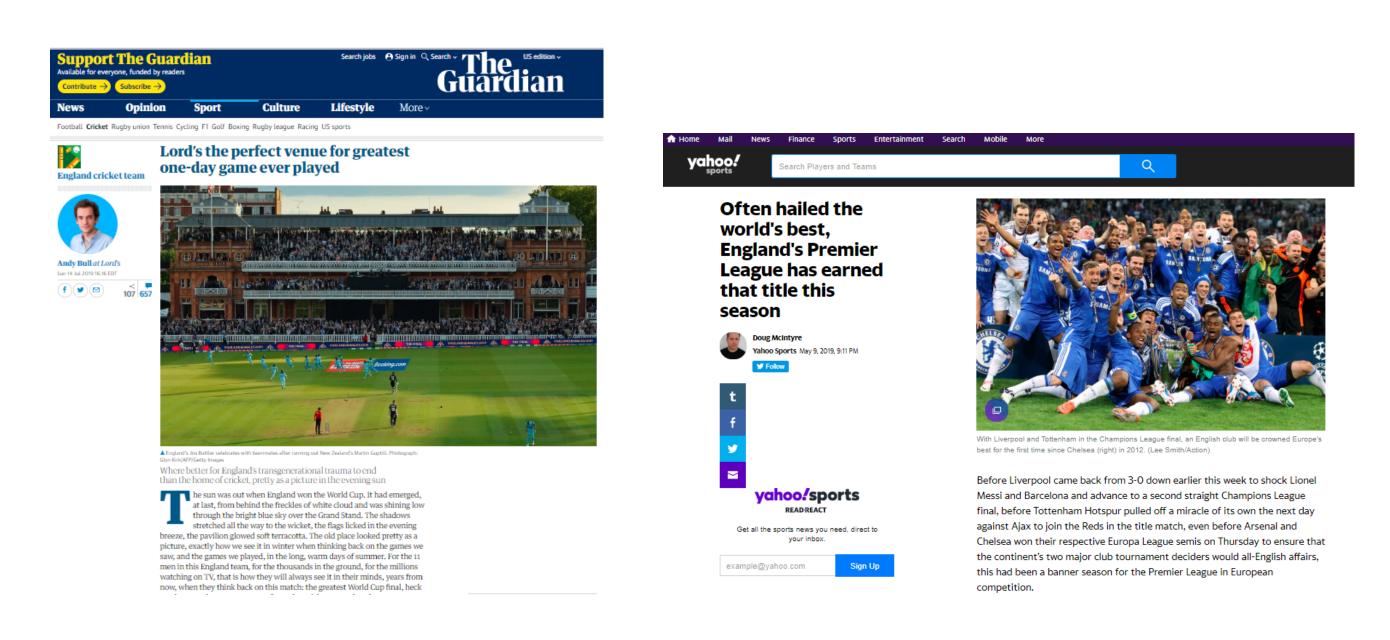




Motivation



- Can we formalize such claims about sports using statistical analysis?
- Can we measure the overall level of skill in a game based on win-loss data from tournaments?

Formal Setup and Goal

- Unknown **PDF of skill levels** P_{α} on interval $[\delta, 1]$ for $\delta > 0$, which is bounded and belongs to η -Hölder class.
- Teams $\{1, \ldots, n\}$ play tournament with unknown i.i.d. skill levels $\alpha_1,\ldots,\alpha_n\sim P_{\alpha}.$
- For $i \neq j$, with probability $p \in (0, 1]$, observe k independent pairwise games where $Z_m(i,j) = \mathbb{I}\{j \text{ beats } i \text{ in } m\text{th game}\}.$
- Bradley-Terry-Luce (BTL) or multinomial logit model [1]:

$$\mathbb{P}(Z_m(i,j) = 1 \mid \alpha_1, \dots, \alpha_n) = \frac{\alpha_j}{\alpha_i + \alpha_j}$$

• Goal: Learn P_{α} from observation matrix $Z \in [0, 1]^{n \times n}$ with

$$Z(i,j) = \begin{cases} \frac{1}{k} \sum_{m=1}^{k} Z_m(i,j), & \text{if games observed bet} \\ 0, & \text{otherwise}. \end{cases}$$

• **Overall skill score:** Negative differential entropy of P_{α}

$$-h(P_{\alpha}) = \int_{\delta}^{1} P_{\alpha}(x) \log(P_{\alpha}(x)) \,\mathrm{d}x$$

measures the variation of skill levels of teams in a tournament. • Intuition: Concentrated P_{α} has high score and outcomes of games are unpredictable; Balanced P_{α} has low score and there is more variation of skill levels.

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Estimation of Skill Distribution from a Tournament

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Estimation Algorithm

tween $i \neq j$,

Input: Observation matrix Z
Output: Estimator
$$\widehat{\mathcal{P}}^*$$
 of P_α
Step 1: Skill parameter estima
rank centrality algorith
1. Construct stochastic matrix $S \in \mathbb{R}^r$
for $i \neq j$, whose rows sum to 1
2. Compute leading left eigenvector $\widehat{\pi}_*$
3. Compute skill level estimates $\widehat{\alpha}_i = \frac{1}{1}$
Step 2: Kernel density estimate
Parzen-Rosenblatt mer
4. Compute bandwidth $h = \Theta(\log(n)^{\overline{2}})$
5. Construct $\widehat{\mathcal{P}}^*$ using appropriate, fixe
 $\widehat{\mathcal{P}}^*(x) \triangleq \frac{1}{nh} \sum_{i=1}^n K(x)$
6. Return $\widehat{\mathcal{P}}^*$

Theoretical Results

Theorem (Mean Squared Error Upper Bound)

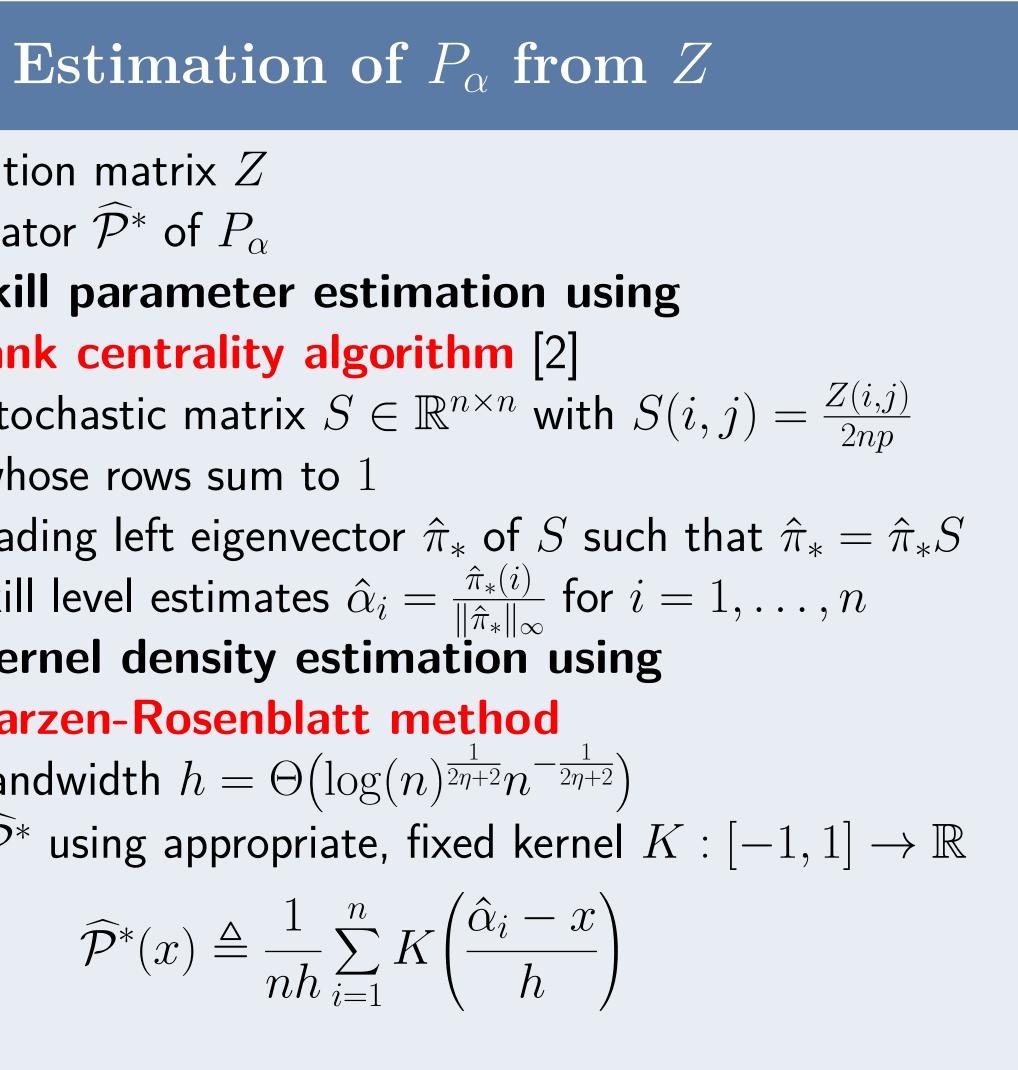
If $p = \Omega(\log(n)/(\delta^5 n))$ and $\lim_{n \to \infty} \delta^{-1}(npk)^{-1/2} \log(n)^{1/2} = 0$, then for all P_{α} ,

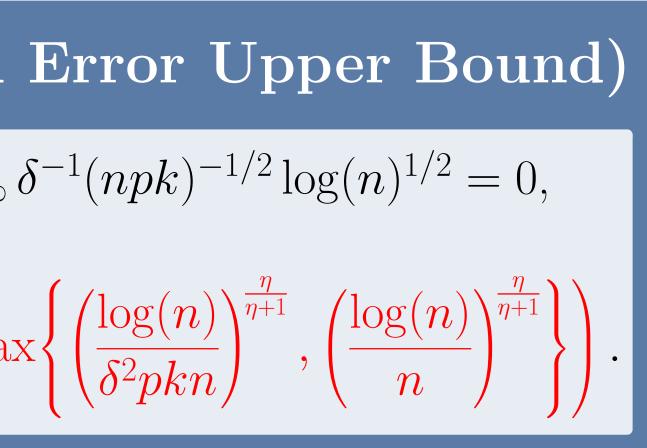
$$\mathbb{E}\left[\int_{\mathbb{R}} \left(\widehat{\mathcal{P}}^*(x) - P_{\alpha}(x)\right)^2 \mathrm{d}x\right] = O\left(\max \frac{1}{2}\right)$$

• Summary of all minimax estimation results:

Estimation prob.	Loss func.	Upp. bound	Low. bound
Smooth skill PDF	MSE	$\tilde{O}(n^{-1+\varepsilon})$	$\Omega(n^{-1})$
BTL skill levels	ℓ^{∞} -norm	$ ilde{O}(n^{-1/2})$	$\tilde{\Omega}(n^{-1/2})$
BTL skill levels	ℓ^1 -norm	$O(n^{-1/2})$	$\tilde{\Omega}(n^{-1/2})$

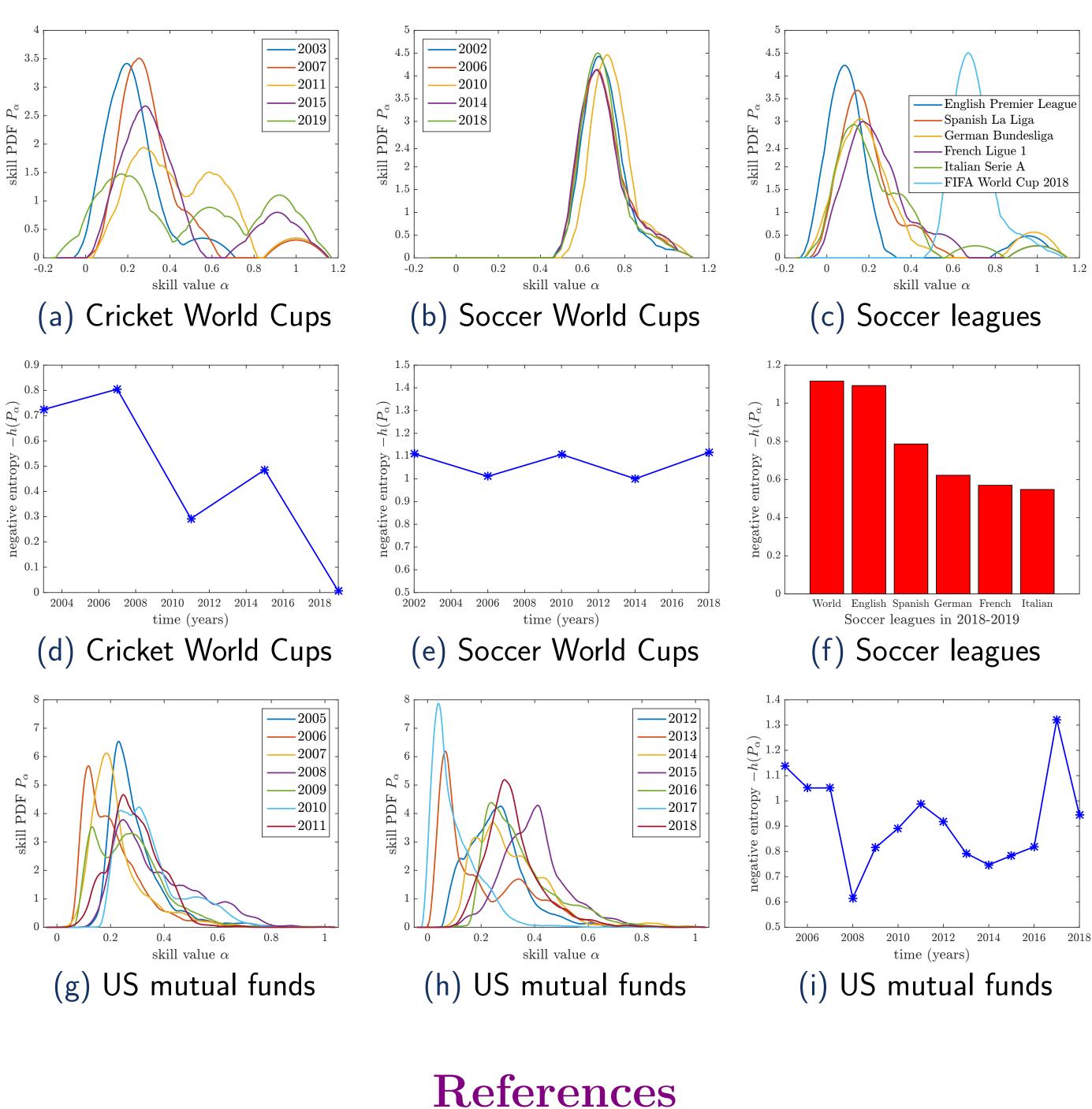
• <u>Note:</u> Our results are in red; other results are known in the literature. Notation \tilde{O} and $\tilde{\Omega}$ hide polylog(n) terms, and $\varepsilon > 0$ is any arbitrarily small constant.





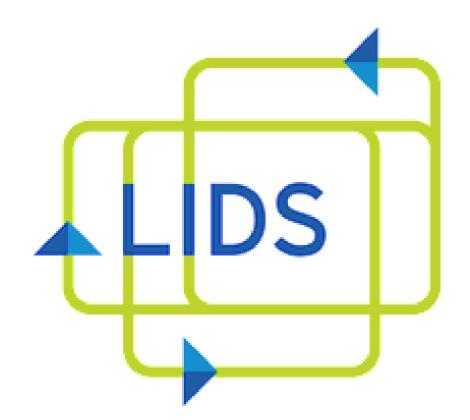
- are decreasing over time.
- dictable over the years.
- that is consistent with fan experience.
- cession of 2008.

Figure: Plots (a), (b), (c), (g), and (h) illustrate *estimated skill PDFs*, and plots (d), (e), (f), and (i) depict corresponding *negative differential entropies*.



- December 1952.
- February 2017.





Experiments

• Cricket world cups: Skill scores of cricket world cup tournaments

• Soccer world cups: Soccer world cups have remained quite unpre-

• Soccer leagues in 2018-2019: Recover ranking of soccer leagues

• US mutual funds: Skill score is minimum during the Great Re-

[1] R. A. Bradley and M. E. Terry, "Rank analysis of incomplete block designs. I. The method of paired comparisons," *Biometrika*, vol. 39, no. 3/4, pp. 324–345,

[2] S. Negahban, S. Oh, and D. Shah, "Rank centrality: Ranking from pairwise comparisons," Operations Research, INFORMS, vol. 65, no. 1, pp. 266–287, January-