

Digital Mindprints

Kenneth W. Regan
University at Buffalo (SUNY)

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- Should “we” cut humans out of the loop in driverless cars? the military? financial trading? other daily applications?
- What are important differences in cognitive tendencies?
- Does each side need to do *xenospection*—building a model of the other's characteristic behavior?

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- Negative side: “E-Doping” by human players. . .

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- Second key: human-computer cognitive differences.

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- US: “Class A” = 1800–2000, “B” = 1600–1800, “C” = 1400–1600,...; adult beginner said to be 600; scholastics down to minimum 100 rating.

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- Also project *standard deviation* and *confidence intervals*.

Context: Decision-Making Model at Chess

- 1 Domain: A set T of decision-making situations t .
Chess game turns

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 - Aggregate statistics: *move-match* **MM**, *equal-top value* **EV**, *average scaled difference* **ASD**, ...
 - Projected confidence intervals: Bernoulli Trials + $|T|$ -adjustment.
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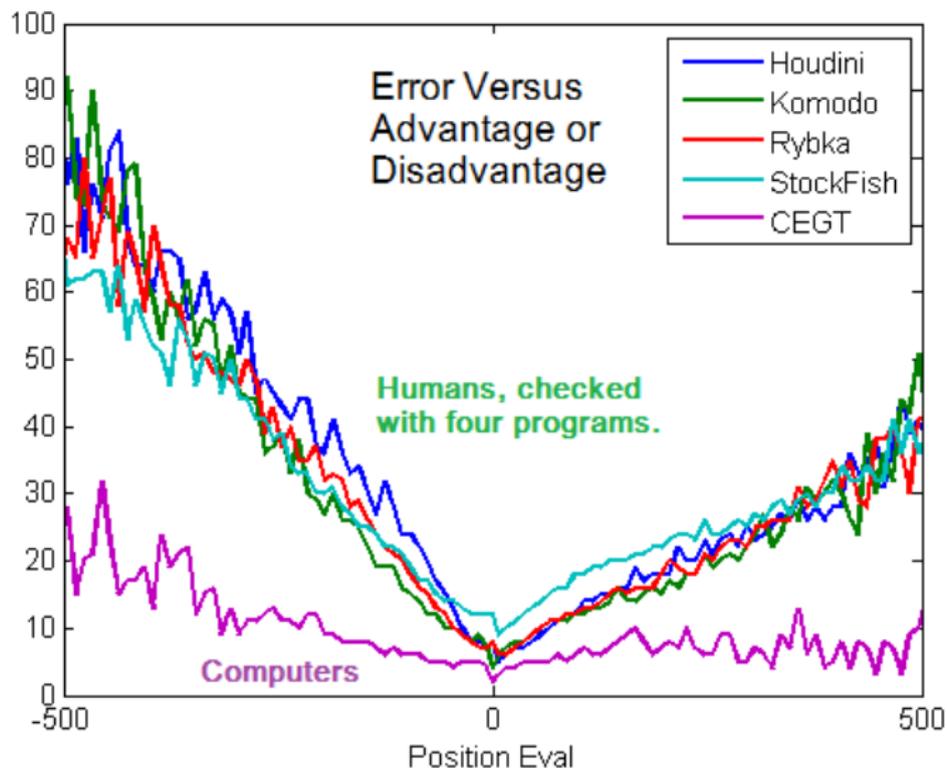
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 - (C) Greater volatility intrinsic to chess as game progresses.

A. Perception Proportional to Benefit

How strongly do you perceive a difference of 500 rupees, if:

- You are buying lunch and a drink in a pub.
- You are buying dinner in a restaurant.
- You are buying an I-pad.
- You are buying a car.

For the car, maybe you don't care. In other cases, would you be equally thrifty?

*If you spend the way you play chess, you care maybe
4× as much in the pub!*

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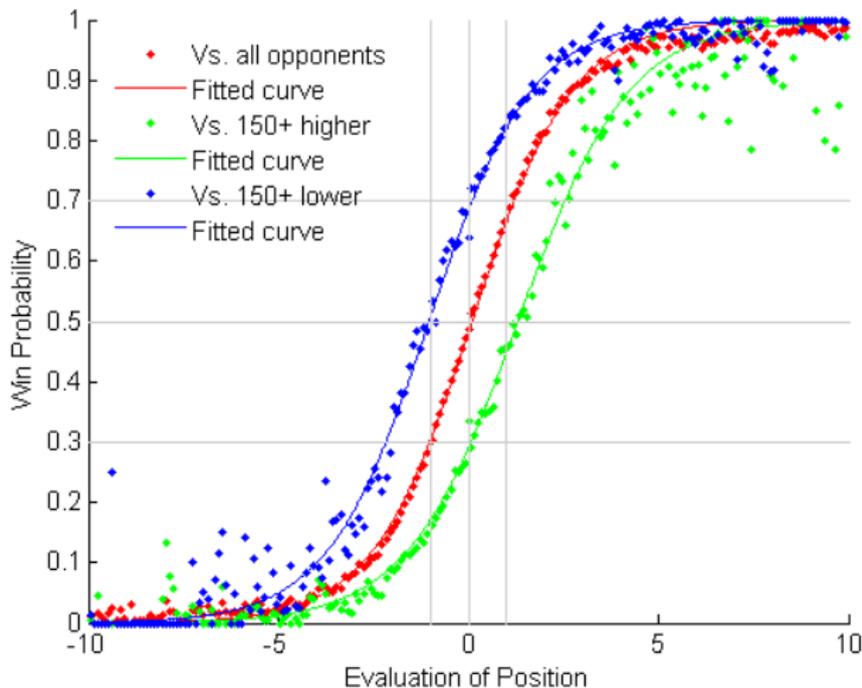
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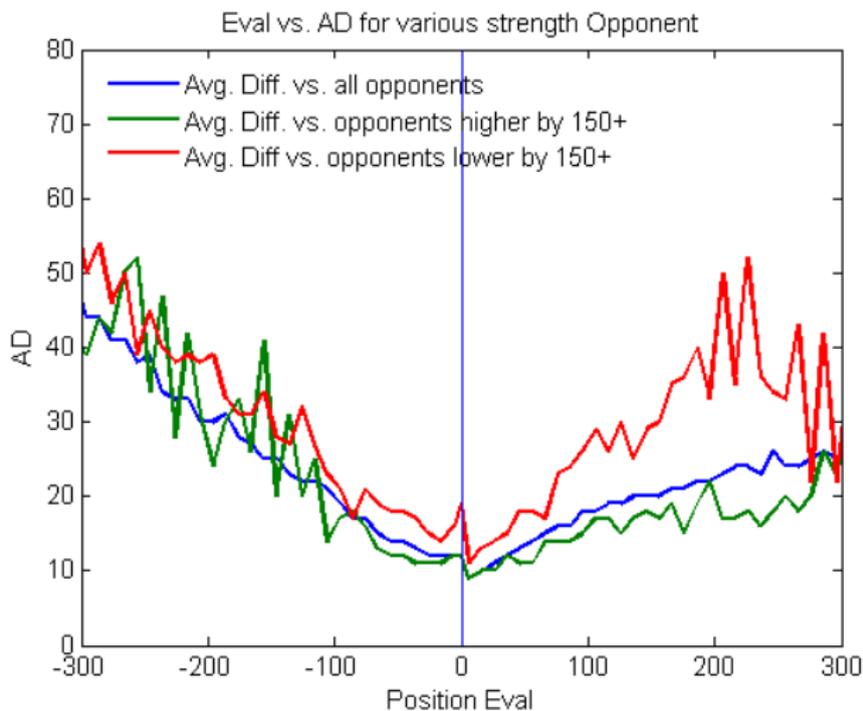
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- Results so far show no shift—

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Eval-Error Curve With Unequal Players



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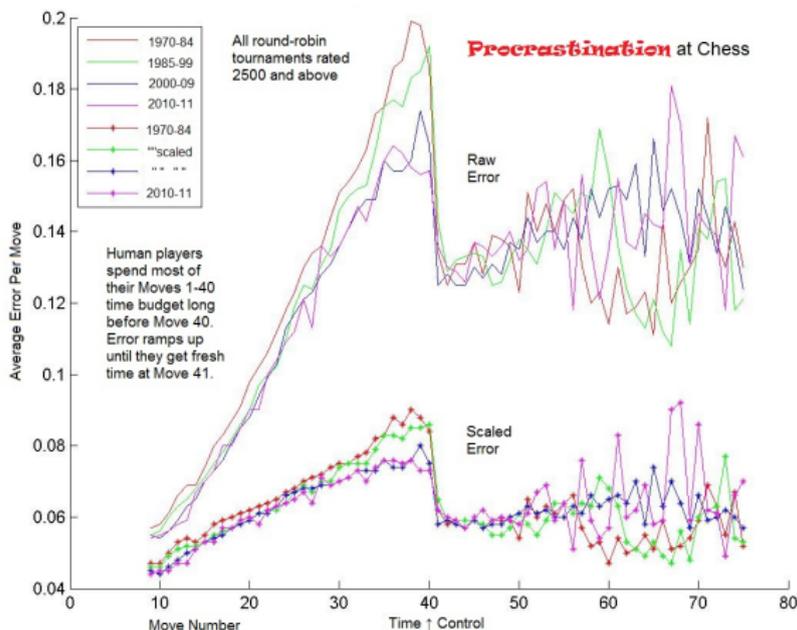
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- [show animations from <https://rjlipton.wordpress.com/2015/10/06/depth-of-satisficing/>]

Procrastination...

Chess players tend to use up most of a ≈ 2 -hour time budget early on, leaving little time for moves 30 to 40 when a fresh budget of time comes. Note ramped-up error until turn 41. (Anand was an exception.)



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Computer and Freestyle IPRs

Analyzed Ratings of Computer Engine Grand Tournament (on commodity PCs) and PAL/CSS Freestyle in 2007–08, plus the Thoresen Chess Engines Competition (16-core) Nov–Dec. 2013.

Event	Rating	2σ range	#gm	#moves
CEGT g1,50	3009	2962–3056	42	4,212
CEGT g25,26	2963	2921–3006	42	5,277
PAL/CSS 5ch	3102	3051–3153	45	3,352
PAL/CSS 6ch	3086	3038–3134	45	3,065
PAL/CSS 8ch	3128	3083–3174	39	3,057
TCEC 2013	3083	3062–3105	90	11,024

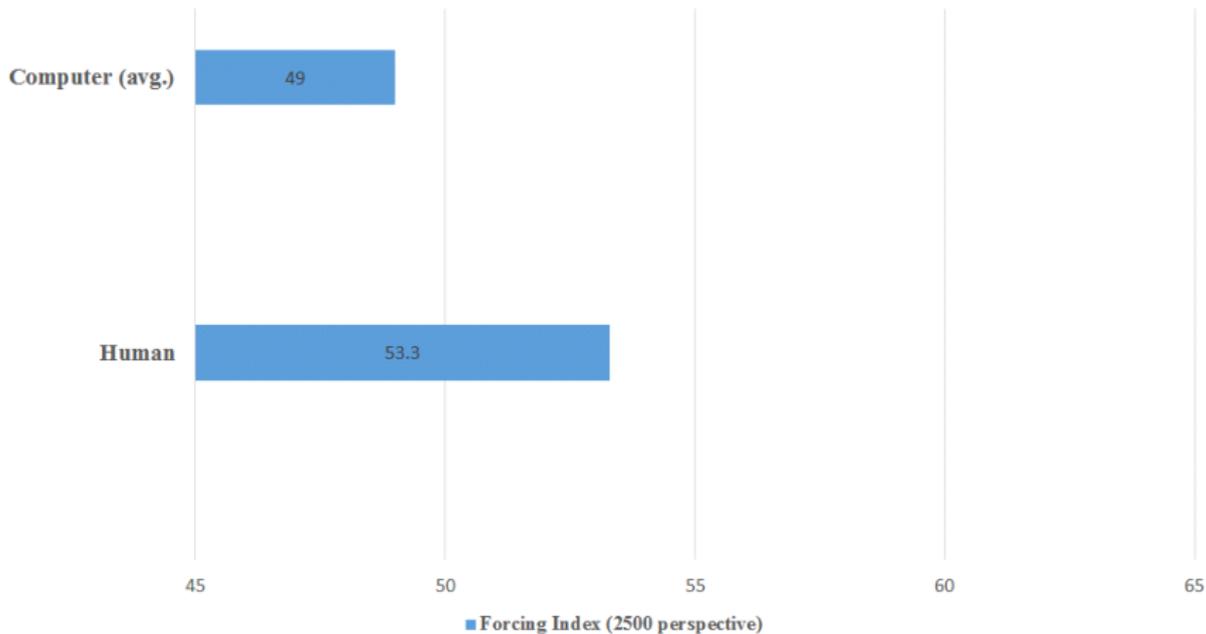
Computer and Freestyle IPRs—To Move 60

Computer games can go very long in dead drawn positions. TCEC uses a cutoff but CEGT did not. Human-led games tend to climax (well) before Move 60. This comparison halves the difference to CEGT, otherwise similar:

Sample set	Rating	2σ range	#gm	#moves
CEGT all	2985	2954–3016	84	9,489
PAL/CSS all	3106	3078–3133	129	9,474
TCEC 2013	3083	3062–3105	90	11,024
CEGT to60	3056	3023–3088	84	7,010
PAL/CSS to60	3112	3084–3141	129	8,744
TCEC to60	3096	3072–3120	90	8,184

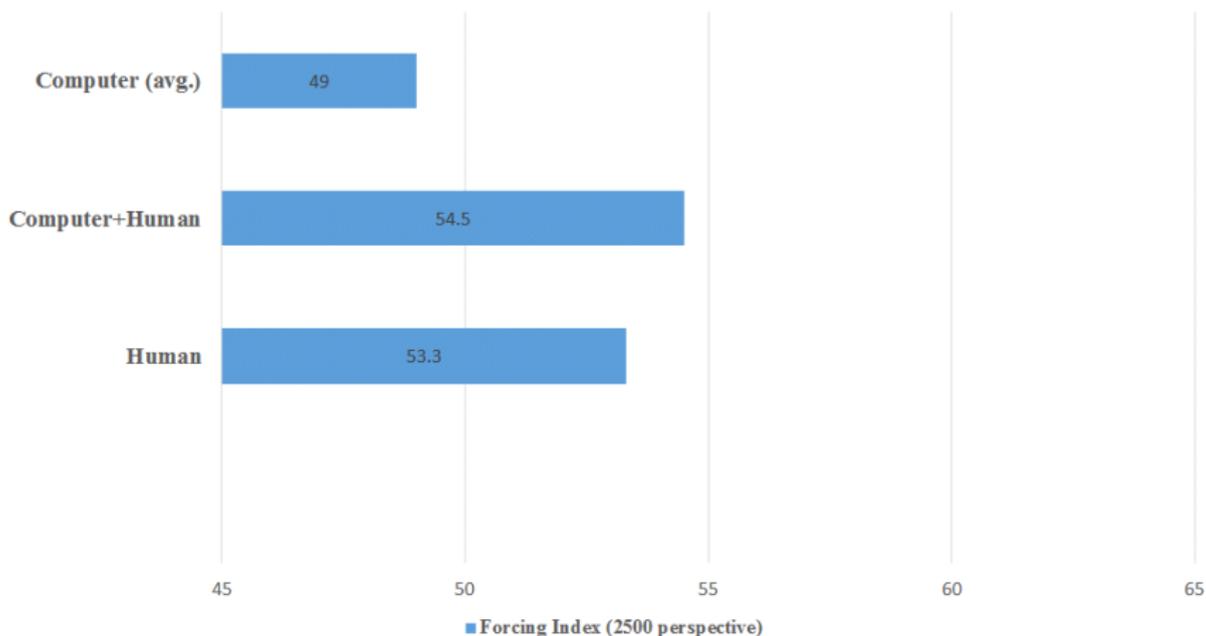
Degrees of Forcing Play

Forcing Index (2500 perspective)



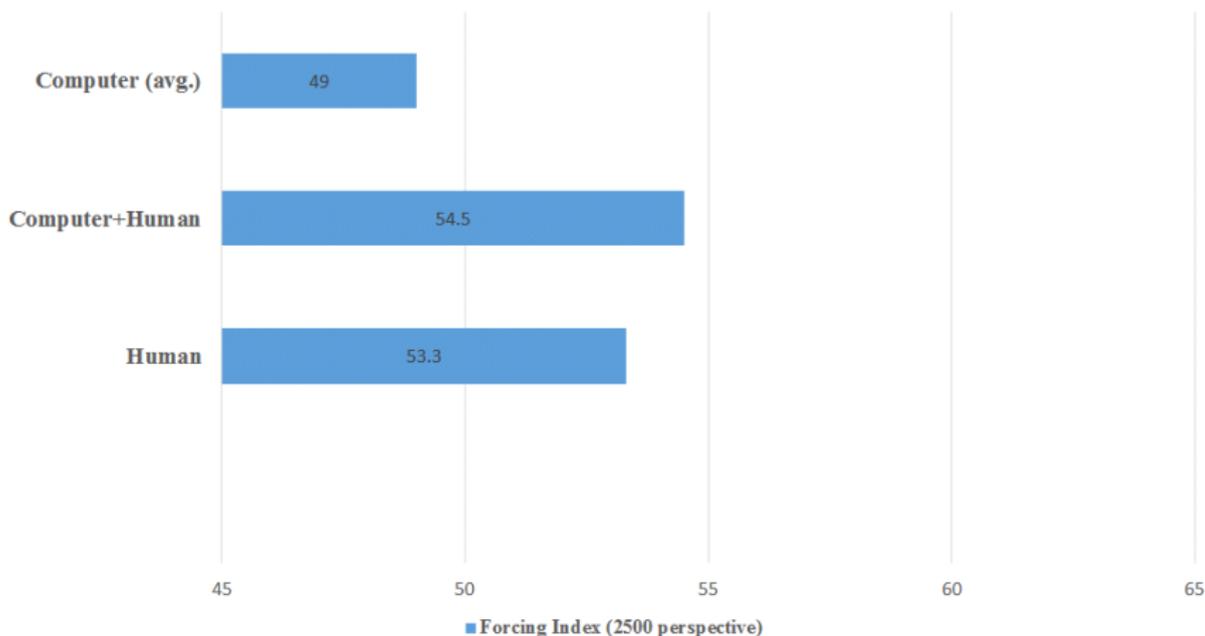
Add Human-Computer Tandems

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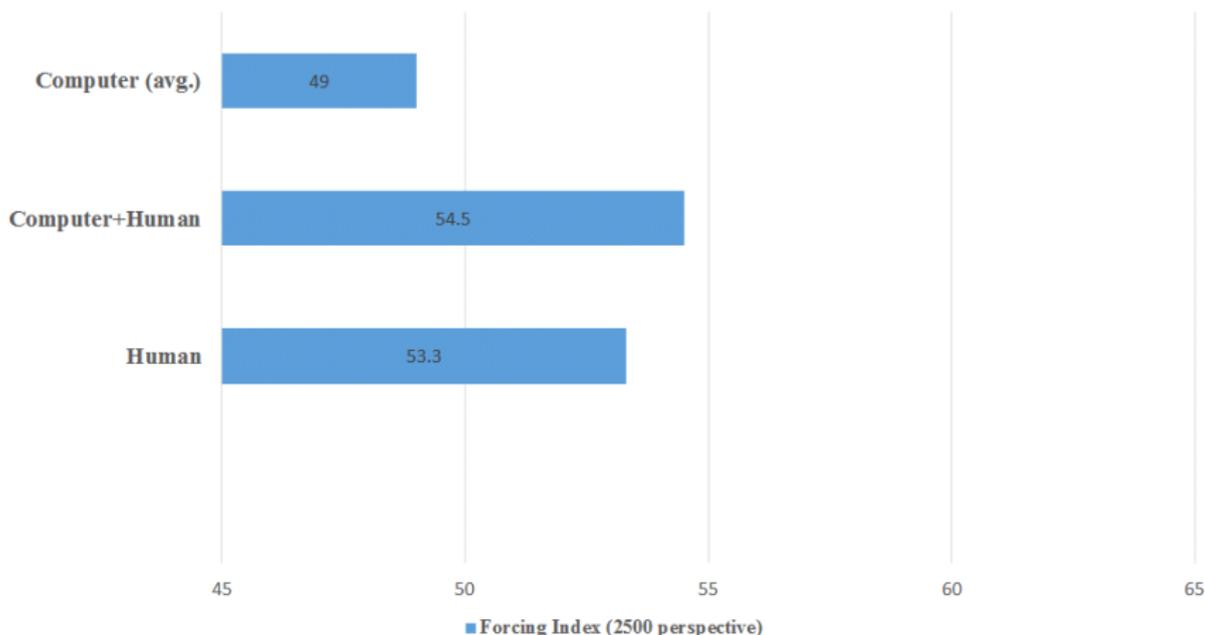
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Evidently the humans called the shots.

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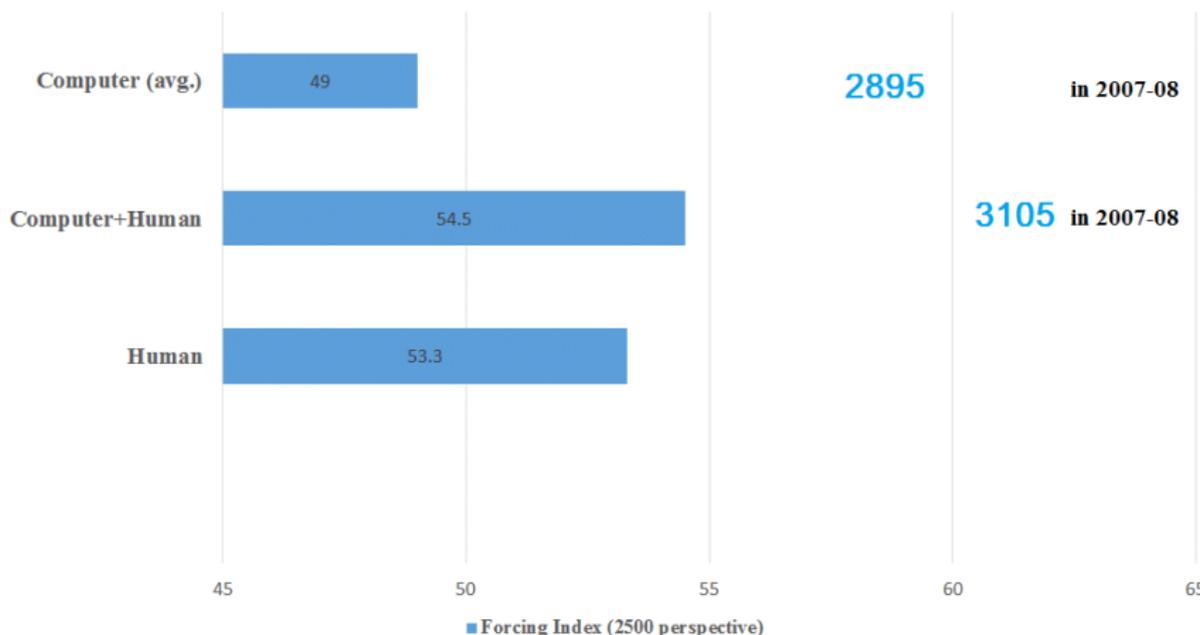
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Evidently the humans called the shots. But how did they play?

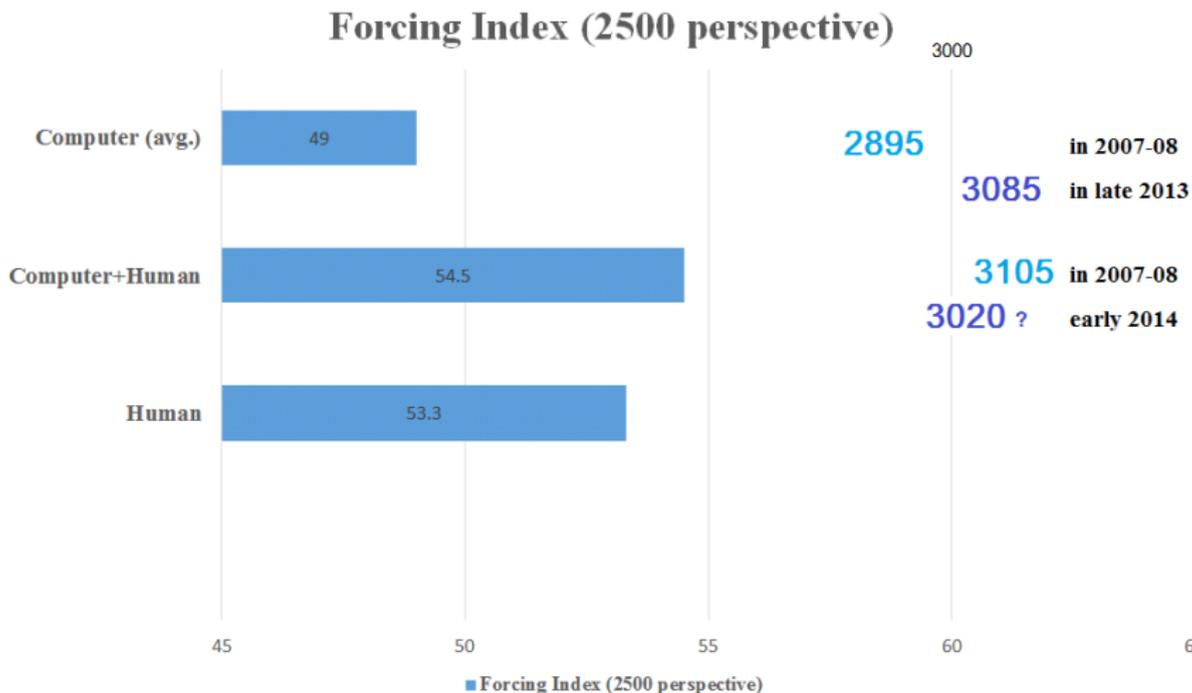
2007-08 Freestyle Performance

Forcing Index (2500 perspective)



Adding 210 Elo was significant. Forcing but good teamwork.

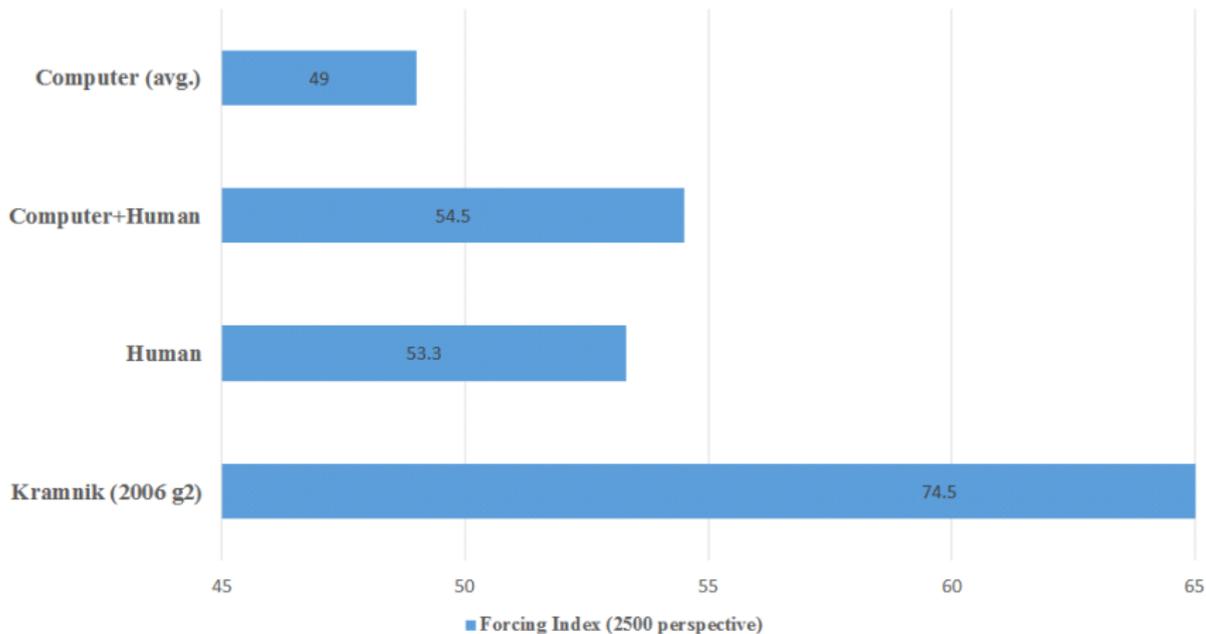
2014 Freestyle Tournament Performance



Tandems had marginally better W-L, but quality not clear...

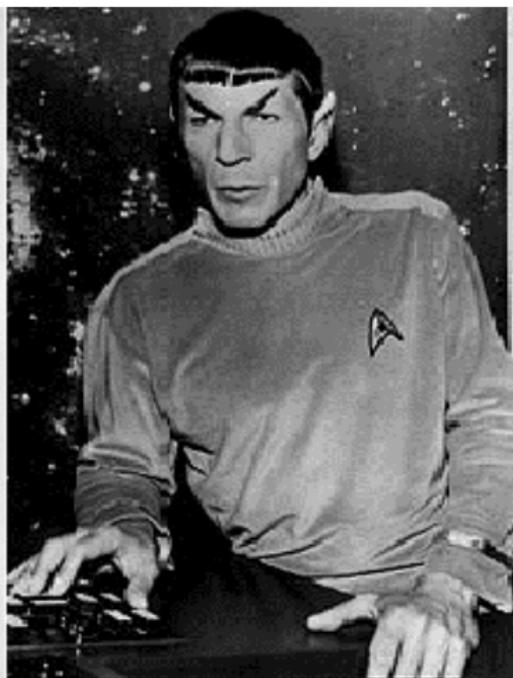
Add Topalov Forcing Kramnik

Forcing Index (2500 perspective)

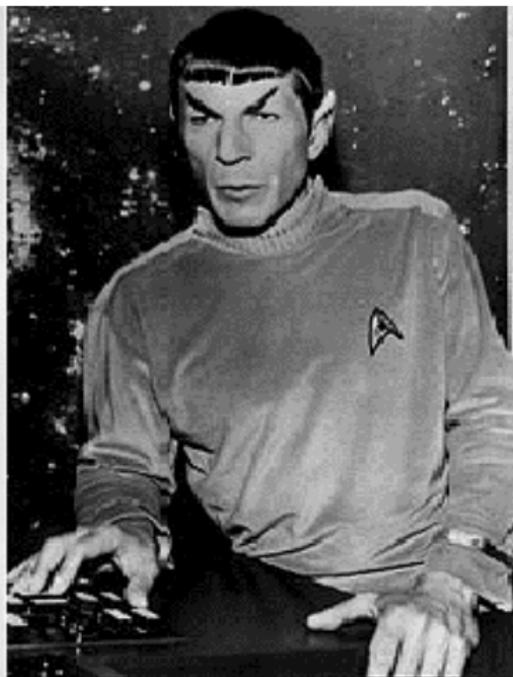


Last bar goes way off the chart

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"It is logical to cultivate multiple options."

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- ⑤ **Main takeaway:**

It should be **natural** to program digital assistants so they enhance our freedom rather than constrain it.

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- Thank you very much for the invitation.