Statistical Pitfalls and Lessons from a Model of Human Decision-Making at Chess

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[1] Joint work with Tamal Tanu Biswas and with grateful acknowledgment to UB's Center for Computational Research (CCR)

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- My statistical model has many other uses. My current CSE712 seminar may help to sharpen it.

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Bxd7	048	034	-033	-033	-013	-042	-039	-050	-025	-010	001	000	-009	-027	-018	000	000	000	000
Qg8	114	114	-037	-037	-014	-014	-022	-068	-008	-056	-042	-004	-032	000	-014	-025	-045	-045	-050
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- *These values are* (currently) *the only chess-specific inputs.*

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5. Derived Outputs:
   - **MM%, EV%, AE** and other aggregate statistics.
   - Projected confidence intervals for them—via Multinomial Bernoulli Trials plus an adjustment for correlation between consecutive turns.
   - **Intrinsic Performance Ratings** (IPRs) for the players.

How the Model Operates

- Given $s, c, \ldots$ and each legal move m_i with value v_i (at top depth), the model computes a *proxy value*

$$u_i = g_{s,c}(\delta(v_1, v_i)),$$

where $\delta(v_1, v_i)$ scales down the raw difference $v_1 - v_i$ in relation to the overall position value v_1, and $g = g_{s,c}$ is a family of curves giving $g(0) = 1$, $g(z) \to 0$.

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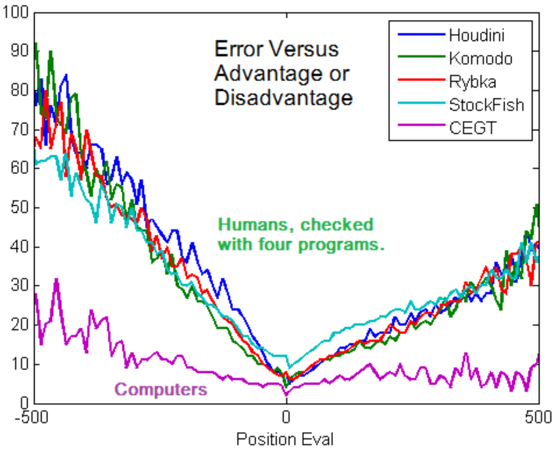
$$\frac{h(p_i)}{h(p_1)} = u_i = \exp(-\left(\frac{\delta(v_1, v_i)}{s}\right)^c).$$

- *Any such value-based model entails* $v_1 = v_2 \implies p_1 = p_2$.

Why the Scaling?



Scaling $\delta(u, v) = \int_{x=u}^{x=v} \frac{1}{1+Cx}\,dx$ (for $x > 0$) levels out differences.

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- The 2-parameter model is fitted simply by setting the projected MM% and ASD equal to the sample means.

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- X = *values of chess moves.*
- Y = *performance indicators* of (human) players:
  - **MM%** = how often the player chose the move listed first by the engine in value order.
  - **EV%** = how often the player chose the first move or one of equal value, as happens in 8–10% of positions.
  - **ASD** = the average scaled difference in value between the player's chosen move m_i and the engine's first move m_1.
- Z = Elo rating
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- Resulting EV estimator is biased "conservatively" (against false positives).

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- How about *my* ESP test??

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Conditioned on one of the top two moves being played, if their values (old: Rybka 3, depth 13; new: Stockfish and Komodo, depths 19+) differ by...:

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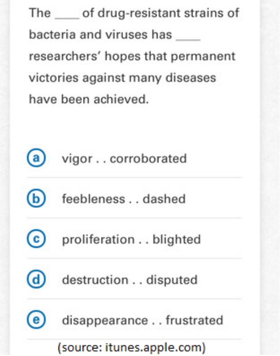
- Relation to slime molds and other "semi-Brownian" systems?

History and “Swing” over Increasing Depths



The ____ of drug-resistant strains of bacteria and viruses has ____ researchers’ hopes that permanent victories against many diseases have been achieved.

(a) vigor . . corroborated

(b) feebleness . . dashed

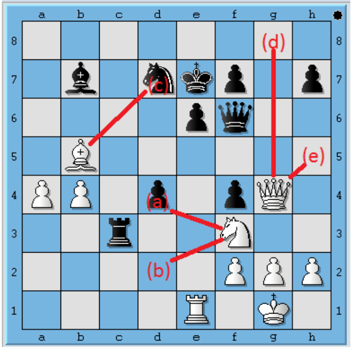
(c) proliferation . . blighted

(d) destruction . . disputed

(e) disappearance . . frustrated

(source: itunes.apple.com)

=



Move	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Nd2	103	093	087	093	027	028	000	000	056	-007	039	028	037	020	014	017	000	006	000
Bxd7	048	034	-033	-033	-013	-042	-039	-050	-025	-010	001	000	-009	-027	-018	000	000	000	000
Qg8	114	114	-037	-037	-014	-014	-022	-068	-008	-056	-042	-004	-032	000	-014	-025	-045	-045	-050
...			...			...			...			...			...			...	
Nxd4	-056	-056	-113	-071	-071	-145	-020	-006	077	052	066	040	050	051	-181	-181	-181	-213	-213

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- Will also separate *performance* and *prediction* in the model.

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Value range	#pos	d10	d15	d20	#pos	d10	d15	d20
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-0.20 to -0.11	5,048	11	10	13	5,177	6	9	11
-0.20 to -0.01	4,677	11	13	16	5,552	8	9	16
0.00 exactly	9,168	24	25	28	9,643	43	40	38
+0.01 to +0.10	4,283	6	1	2	5,705	8	3	2
+0.11 to +0.20	5,198	7	5	3	5,495	10	5	3
+0.21 to +0.30	5,200	7	2	1	4,506	3	4	2

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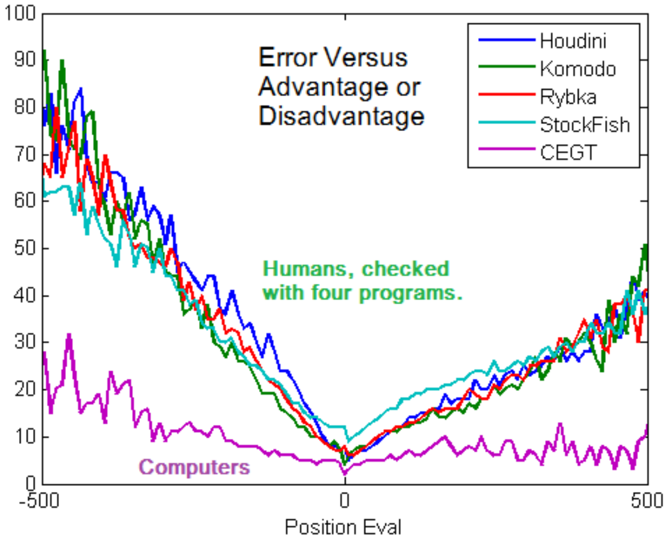
- **Segue to posts on the *Gödel's Lost Letter* blog:**

"Unskewing the Election"
"Stopped Watches and Data Analytics"

Extras: Human Versus Computer Phenomena



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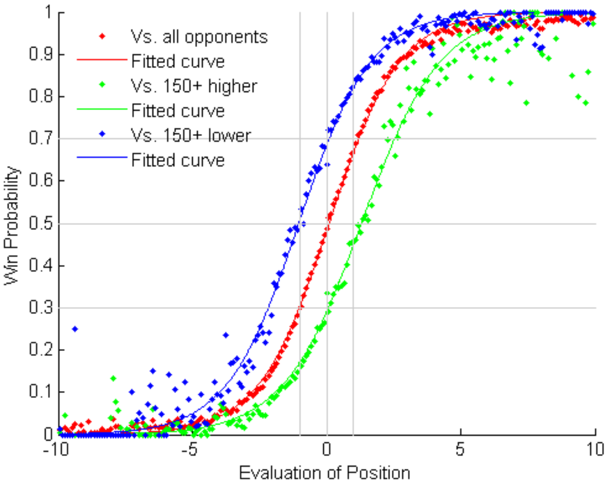
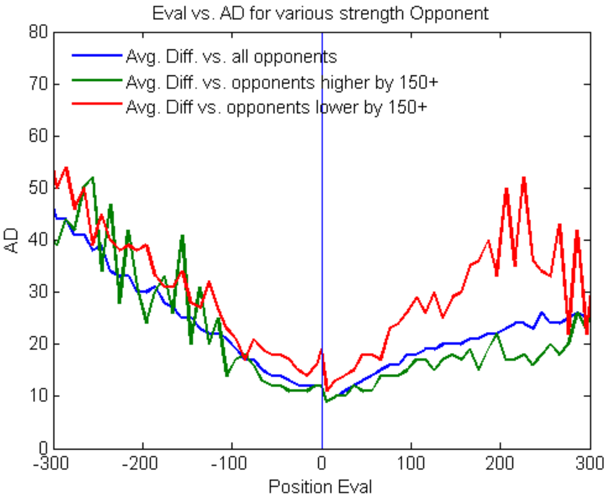


Eval-Error Curve With Unequal Players



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.

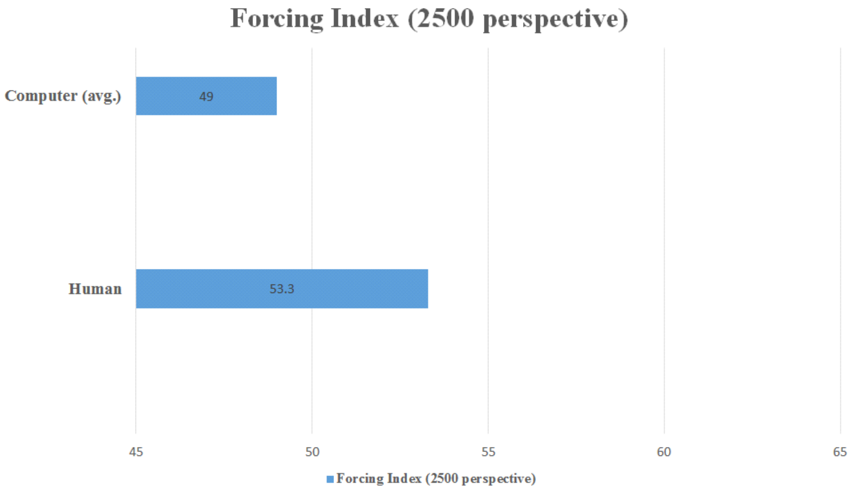
Event	Rating	2σ range	#gm	#moves
CEGT g1,50	3009	2962–3056	42	4,212
CEGT g25,26	2963	2921–3006	42	5,277
PAL/CSS 5ch	3102	3051–3153	45	3,352
PAL/CSS 6ch	3086	3038–3134	45	3,065
PAL/CSS 8ch	3128	3083–3174	39	3,057
TCEC 2013	3083	3062–3105	90	11,024

Computer and Freestyle IPRs—To Move 60

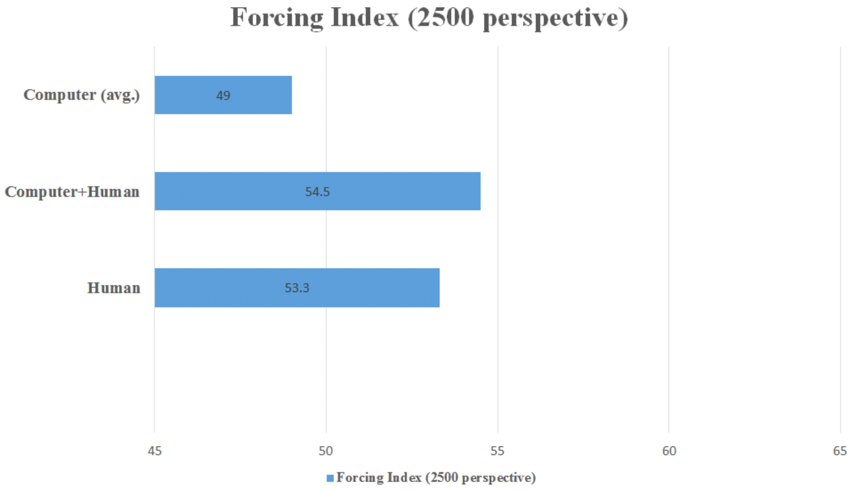
Computer games can go very long in dead drawn positions. TCEC uses a cutoff but CEGT did not. Human-led games tend to climax (well) before Move 60. This comparison halves the difference to CEGT, otherwise similar:

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



Add Human-Computer Tandems



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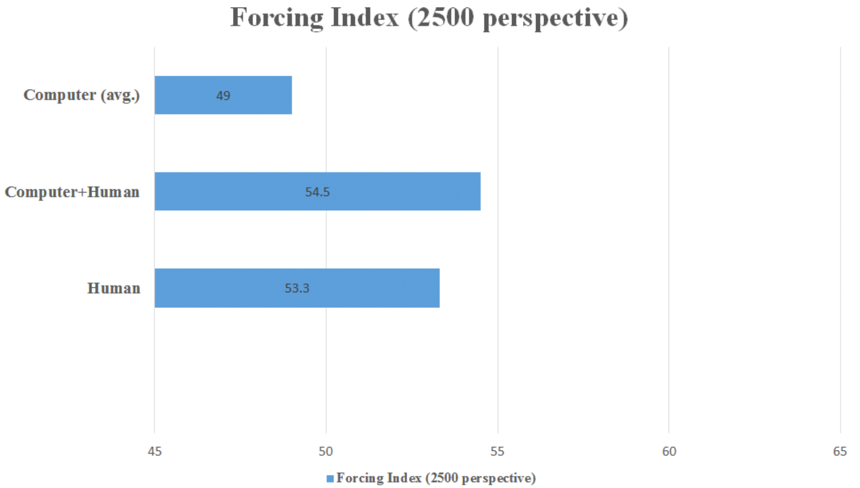

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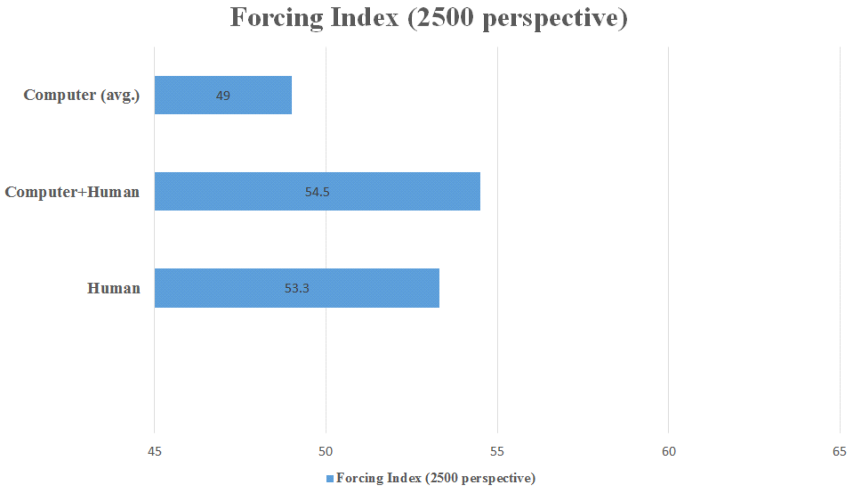
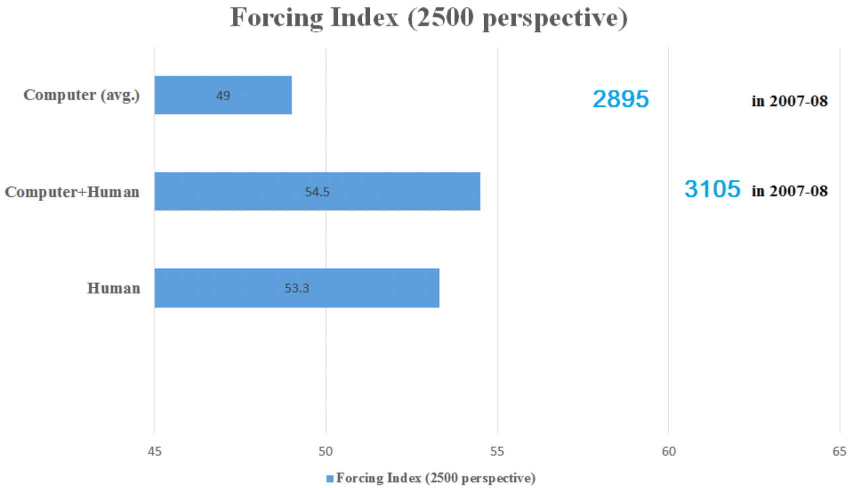


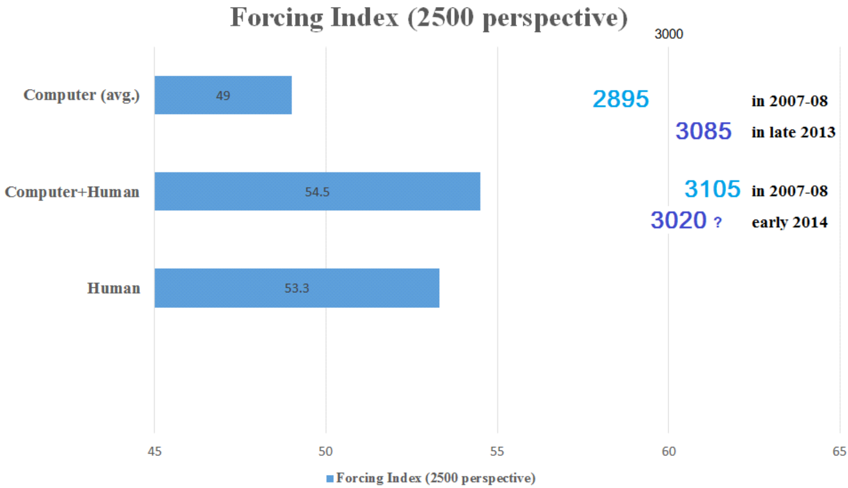
Evidently the humans called the shots. But how did they play?

2007–08 Freestyle Performance



Adding 210 Elo was significant. Forcing but good teamwork.

2014 Freestyle Tournament Performance



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