Cheating Detection and Cognitive Modeling At Chess

Cognitive Science Colloquium

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[1]With grateful acknowledgment to co-authors Guy Haworth and Tamal Biswas, students in my graduate seminars, and UB's Center for Computational Research (CCR)

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- **Multiple-choice tests**: m_i are possible answers to a test question, u_i = gain/loss for right/wrong answer.

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- (a) vigor . . corroborated
- (b) feebleness . . dashed
- (c) proliferation . . blighted
- (d) destruction . . disputed
- (e) disappearance . . frustrated

(source: itunes.apple.com)

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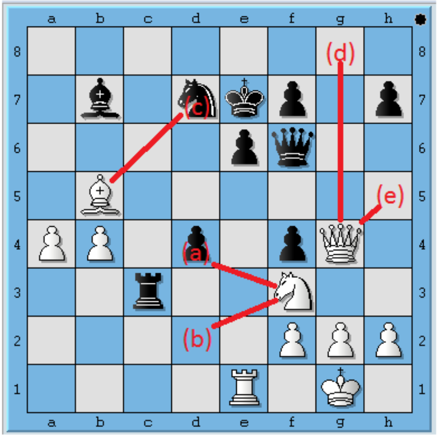

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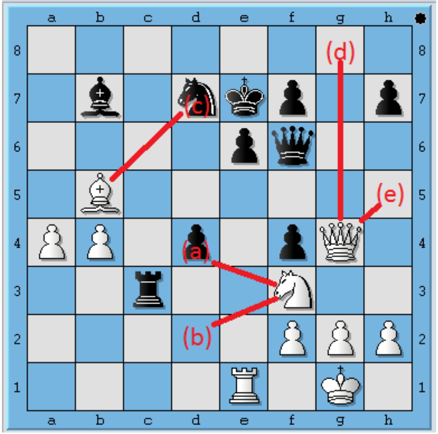

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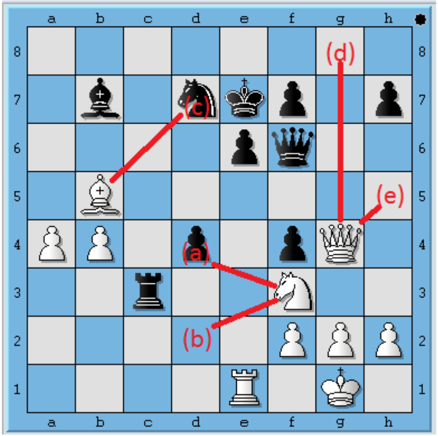

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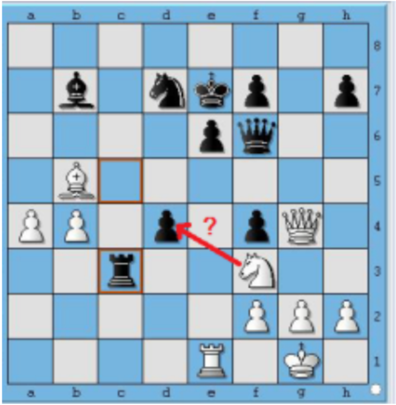
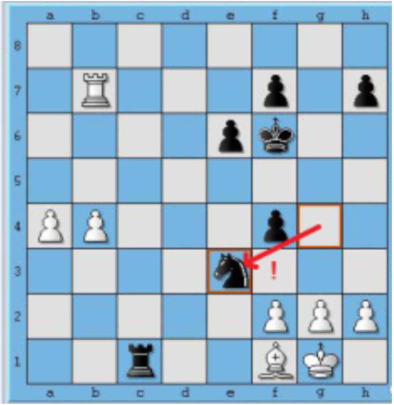
Move Utilities Example (Kramnik-Anand, 2008)





Depths... Values by Stockfish 6

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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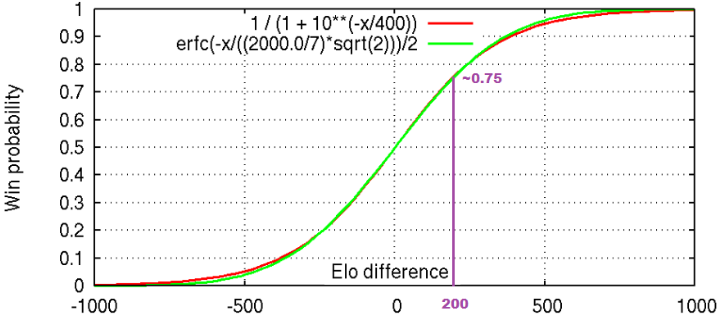
- Expectation $e = \frac{1}{1+\exp(c(R_P - R_O))}$ depends only on difference to opponent's rating R_O. With $c = (\ln 10)/400$ the curve is:



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- Other than these, **my model knows nothing about chess.**

Log-Linear Versus Loglog-Linear Model

The generic **log-linear** model puts

$$\log\left(\frac{1}{p_i}\right) = \alpha + \beta u_i, \quad \text{or equivalently,} \quad \log\left(\frac{1}{p_i}\right) - \log\left(\frac{1}{p_1}\right) = \beta\delta_i,$$

where $\delta_i = u_1 - u_i$. Solved by **softmax** giving $p_i = p_1 \exp(-\beta u_i)$, so each p_i is represented as a **multiple** of the best-move probability p_1.

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In place of $\beta\delta_i$, I have $\left(\frac{\delta_i - h\rho_i}{s}\right)^c$, where the "heave term" ρ_i uses the values at lower depths of search. Why h is tightly clamped.

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- An **Intrinsic Performance Rating** (**IPR**) for the set of games.

Fit s, c, h by making T1,EV,ASD be **unbiased estimators** on the training sets, which are stratified by Elo ratings.

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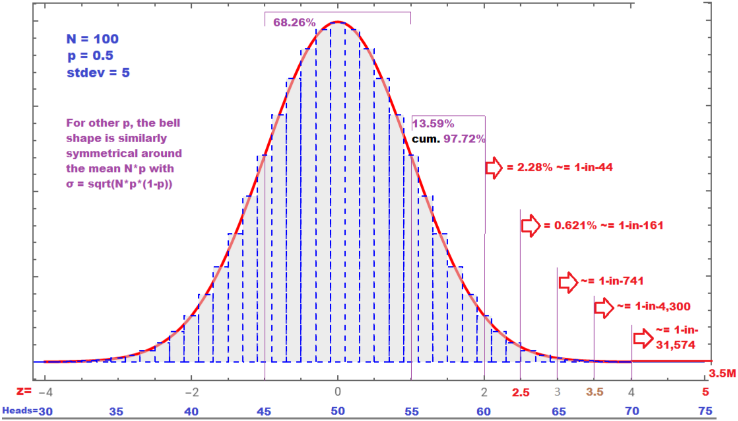
- $3\sigma = 740$–1;
- $2\sigma = 43$–1 (civil minimum standard, polling "margin of error").

Bell Curve and Tails



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Are these considerations orthogonal, or do they align?

Over large datasets from (presumably) non-cheating players, the **Central Limit Theorem** "kicks in" well: the z-scores conform to the bell curve.

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6. How can we distinguish *uncovering genuine cognitive phenomena* from *artifacts of the model*?

Show demos as time allows...

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Let's consider elements of **difficulty** and **time pressure**.

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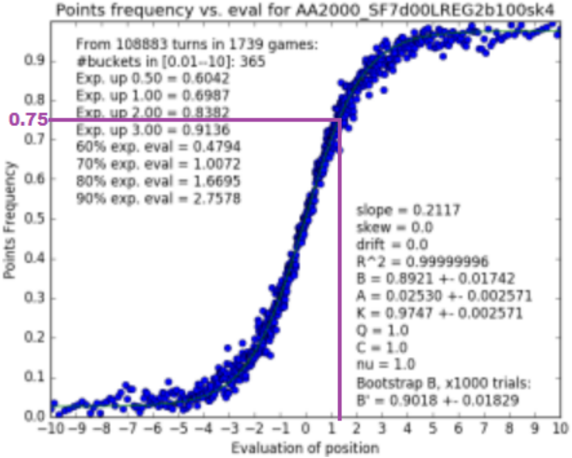

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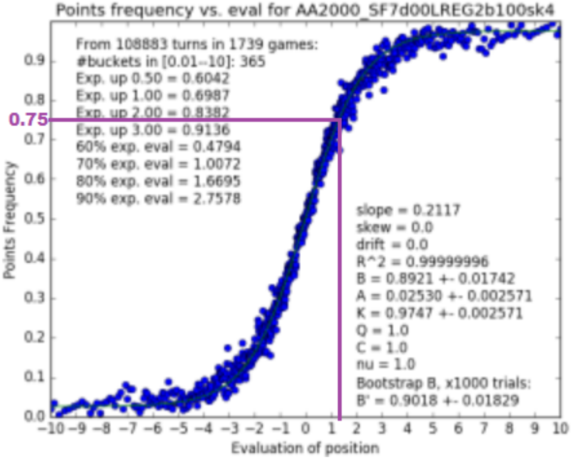

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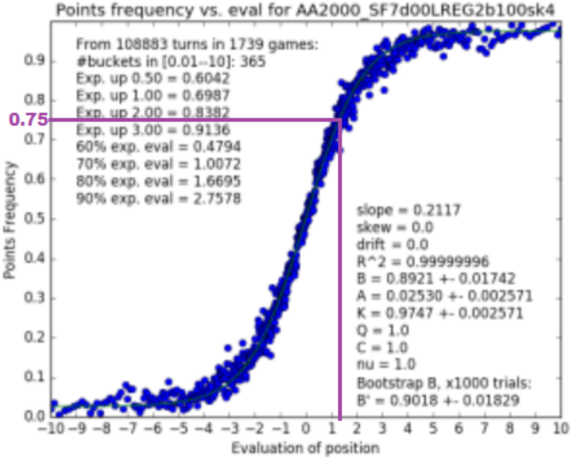

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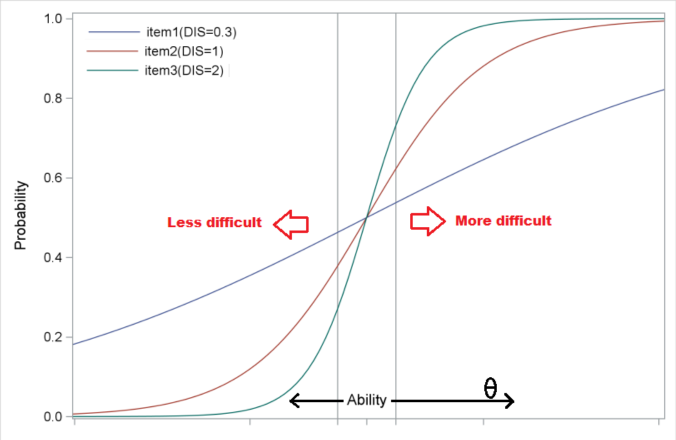
- Complication: dependence on rating itself.

Item-Response Theory (IRT source)



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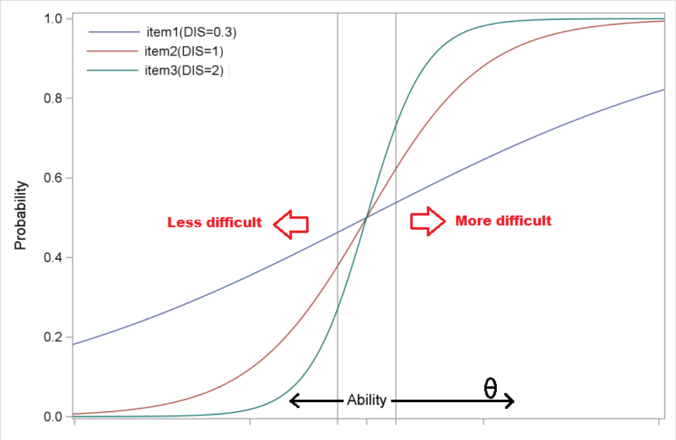

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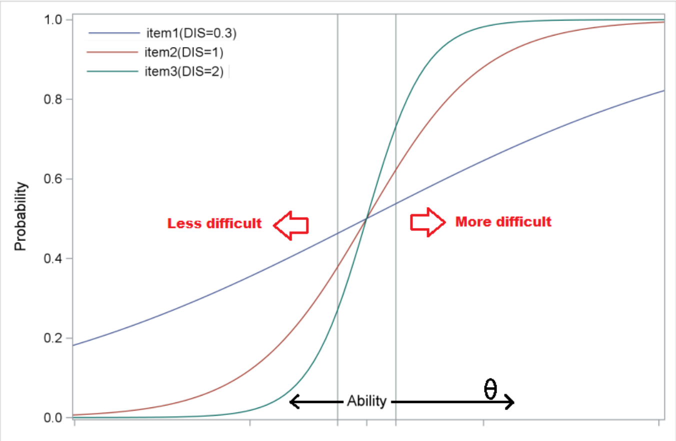

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- Slope at $y = 0.5$ *correctness rate* is the **discrimination** factor.

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- How well does hazard—normalized over aptitude—work as a measure of difficulty?

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How about IPR?

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- With $\geq 2x$ hazard: **2170 +- 115**. Could be consistent. **But—**
- Positions of of $0.5x$ or lower hazard: **1800 +- 180**.
- Not constancy of signal.

IPR and Hazard (World Senior Teams 2024)

- Older players, established ratings (but deflated), average **2080**.
- Focus on **2000–2200**. Analysis by Stockfish 11 in **EWN** mode.
- IPR overall: **2125 +- 40**. Broken down according to [dis-]advantage:
  - 1–2 pawns behind: **2170 +- 105**; worse: **2065 +- 110**.
  - 1–2 pawns ahead: **2085 +- 120**; better: **2020 +- 155**
  - Within 1.00 of equal: **2145 +- 45**; within 0.50: **2125 +- 65**.
- Reasonable constancy of signal.
- But on positions with $\geq$ 1.5 times normal hazard: **2255 +- 65**.
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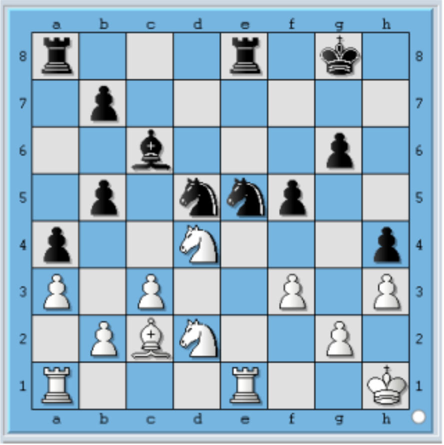
- Positions of of $0.5x$ or lower hazard: **1800 +- 180**.
- Not constancy of signal.
- Low-hazard positions either have an obvious best move or many good moves.

Example: Niemann-Shankland, USA Ch. 2023



Depths	1	2	3	...	18	19	20	21	22	23
Rad1	+041	+035	+029		-067	-068	-070	-070	-071	-071
Rab1	+016	+009	+021		-061	-067	-070	-070	-071	-071
Ne2	-048	-091	-040	...	-070	-070	-070	-071	-071	-071
Reb1	-030	-052	-010		-068	-070	-070	-071	-071	-071
Ra2	-003	-029	-010		-068	-070	-070	-071	-071	-071
Rf1	-029	-080	-010		-067	-070	-070	-071	-071	-071
Red1	-006	-057	-010		-067	-069	-070	-071	-071	-071
Nf1	+017	-029	-062		-080	-069	-070	-071	-071	-071
Rac1	+018	+012	+021	...	-067	-070	-070	-071	-071	-071
Rec1	-029	-052	-010		-067	-070	-071	-071	-071	-071
Rg1	-030	-044	-008		-067	-070	-071	-071	-071	-071
Re2	+008	+022	+035		-067	-069	-071	-071	-071	-071
Kg1	+021	+022	+028		-067	-069	-071	-071	-071	-071
Kh2	+022	+022	+013		-066	-069	-071	-071	-071	-071
Nxc6	-044	-044	-030		-088	-094	-086	-095	-089	-097
b3	-076	-076	-062	...	-101	-132	-120	-104	-118	-113
...										

Low-hazard because crisis is far off, but difficult in real chess terms. Low E_L, high entropy H. (Niemann lost.)

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   - Carow and Witzig [CW, Feb. 2024] consider all the above, but strive for human-chess based measures.

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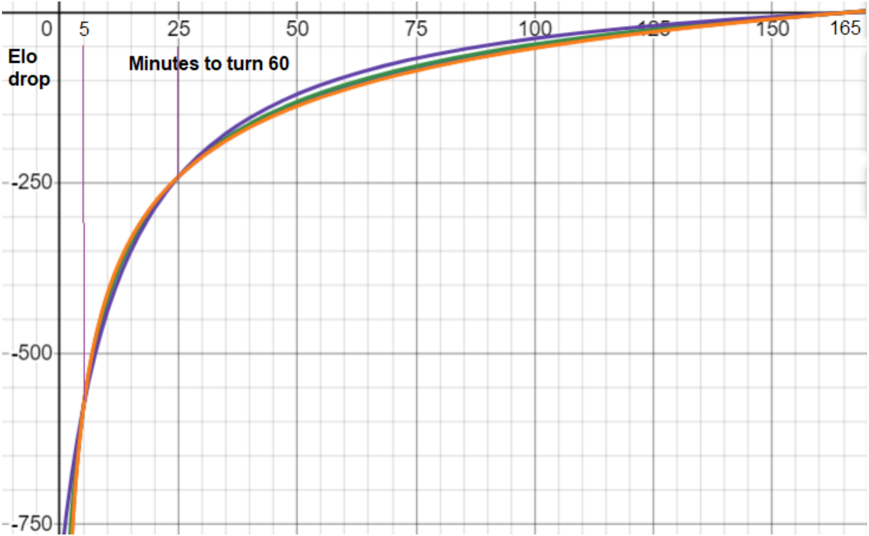
Time-Quality Curves (whole graph)



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- Vivid reproduction of [SZS 2022] (and also Anderson et al., 2016 thru now for online blitz).

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Discussion and Q & A

[And Thanks]

[Possible extra slides for Q & A follow...optional, of course...]

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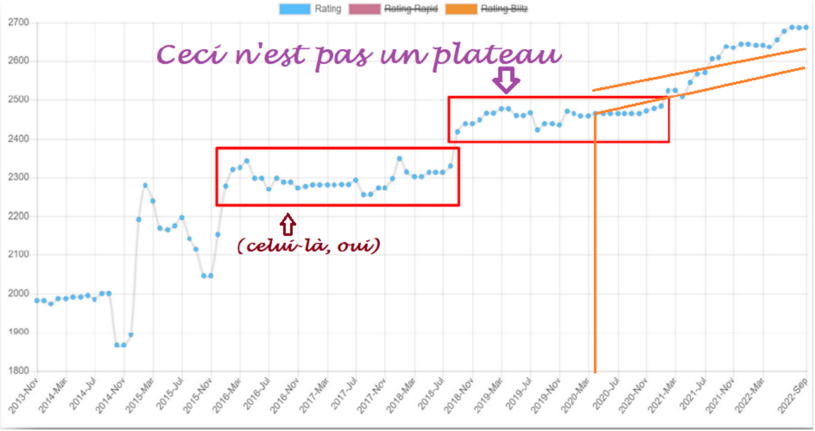
Hans Niemann: Platform or Plateau?



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- **Q&A**, and **Thanks**.