Chess Research and Public Interests

New Faculty Academy 2026

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8 April, 2026

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

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- Tenure and great colleagues conferred blessings of Freedom...

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- Then came the Topalov-Kramnik 2006 World Championship Scandal.

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7. Find people to talk to...and compare results.

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  - We will try to glean comparable insight from numerical analytics.

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

Chess and Tests—With Partial Credits (Or LLMs?)

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- (a) vigor . . corroborated
- (b) feebleness . . dashed
- (c) proliferation . . blighted
- (d) destruction . . disputed
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(source: itunes.apple.com)

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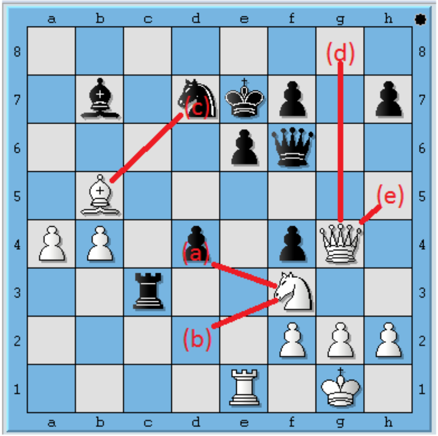

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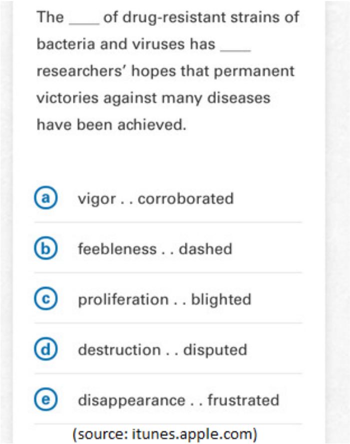
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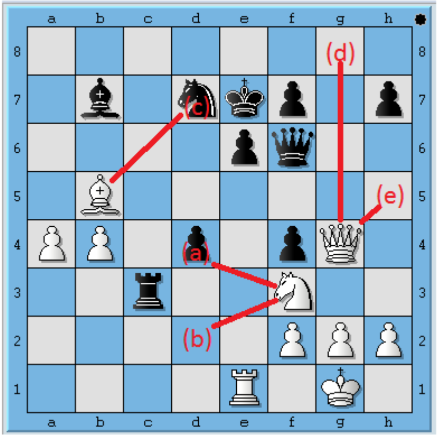

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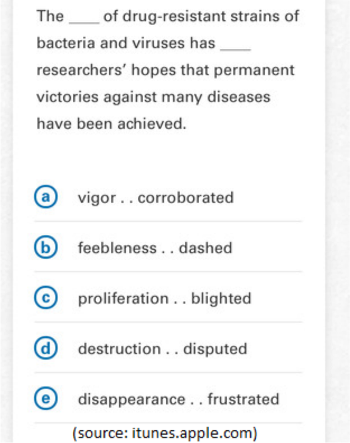
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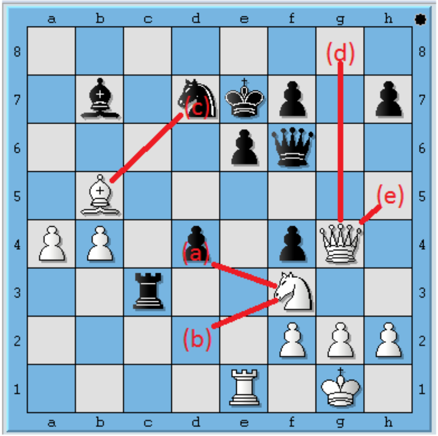

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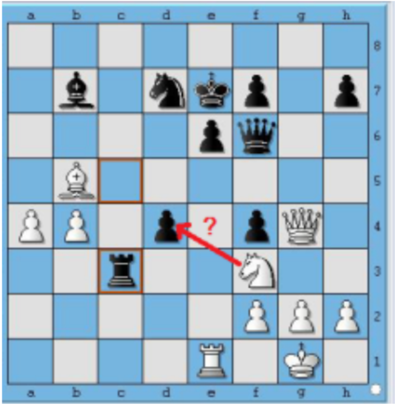
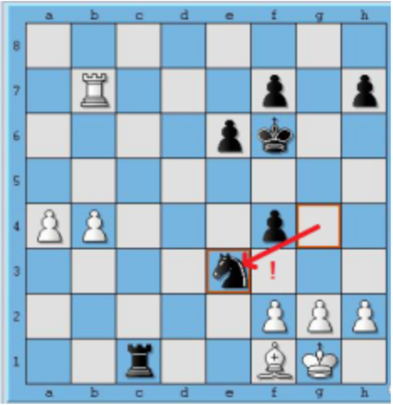
Move Utilities Example (Kramnik-Anand, 2008)





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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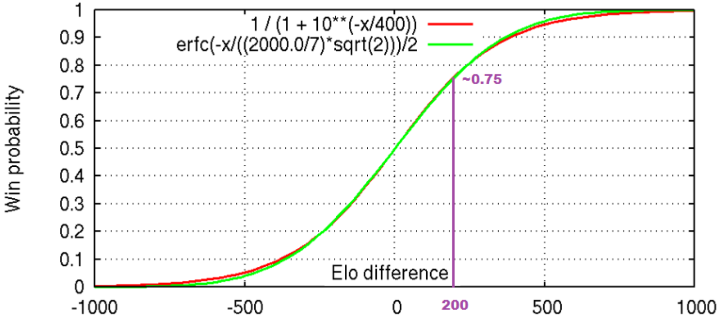
- Expectation given by rating *difference* via this logistic curve:



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Main Parameters and Inputs

The (only!) player parameters trained against chess Elo Ratings are:

- s for "sensitivity"—strategic judgment. *Like Anatoly Karpov.*
- c for "consistency" in tactical minefields. *Like Mikhail Tal.*
- h for "heave" or "Nudge"—obverse to depth of thinking.

Trained on all available in-person classical games in 2010–2019 with both players near the same Elo marker 1025, 1050, . . . , 2775, 2800, 2825.

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

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The generic **log-linear** model puts

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

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- So p_i are represented as **powers** of the best-move probability p_1.
- In place of $\beta\delta_i$, I really have $\left(\frac{\delta_i - h\rho_i}{s}\right)^c$, with h tightly clamped.

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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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- Q & A — And Thanks.