Cheating Detection and Cognitive Modeling at Chess

CS Distinguished Lecture, Northwestern University

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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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- (*The model does track how the calculated values of moves change as the engine progresses through *depths of search*.)

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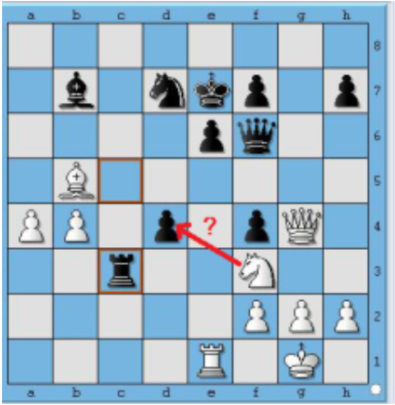
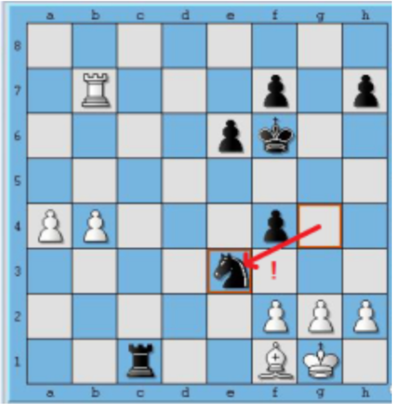
- Other Q: How do computer evaluations translate to chances of winning?

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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- **ASD**: Make the *scaled* "average centipawn loss" asd_a of a player's moves $m_{i_t,t}$—as judged by the testing engine—equal

$$asd_{proj} = \sum_{t=1}^{T} \sum_{i=1}^{\ell} p_{i,t}\delta_{i,t}.$$

Alternative fitting methods include maximum-likelihood estimation, equivalently, minimzing $\sum_{t=1}^{T} \log(\frac{1}{p_{i_t,t}})$.

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- Captures, advancing vs. retreating moves, moves with Knights or other specific pieces...

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- Enables projecting some inferior move as more likely than m_1 in about 15% of positions, improving the "prediction hit" rate by 2–3 percentage points.

Demonstration: 2024 FIDE Candidates Tournaments

(show)

Happy Birthday 29 May to the winners, D. Gukesh and Zhongyi Tan!

Basic Model Sanity Facts

Whereas the fitted log-linear model *grossly underestimates* **M2** and **M3**, the fitted double-log model underestimates them (hence also **T2** and **T3**) only slightly. Moreover:

For each other metric μ, the "ersatz z-test"

$$z_\mu = \frac{\mu_a - \mu_{proj}}{\sigma_\mu}$$

is tolerably close to Gaussian normal $\mathcal{N}(0,1)$ and with considerable independence of other $z_{\mu'}$. This is so both after fitting and under the rating-based testing procedure.

The main quantities z_{T1}, z_{ASD}, and z_{EV} are expressly **adjusted** to conform to the (upper arm of the) bell curve in myriad **randomized resampling** trials over (parts of) the training sets.

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5. ...reproducibility is doubtful and arduous.

The *chess angle* is to trade 1 against wealth of 2,3,4,5: lots of players and games, real competition, clear goals and metrics (Elo ratings), and not only reproducible but conducive to abundant falsifiable predictions.

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

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- 30 minute "lump sum" added after turn 40.

Gives 110 minutes to the turn 40 "time control" and 150 minutes to turn 60.

The Open (Men's) section gave 120 minutes at the start, with 30 minute lump sum after turn 40, **but** 30 seconds increment only after turn 40. Thus the moves up to turn 40 were "classic time pressure" without increment. (Gives only 160 minutes to turn 60.)

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- (From my recent graduate seminar. Q&A phase can begin here.)

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- Correspondence to Multiple-Choice Tests.
- The "Solitaire Chess" feature by Bruce Pandolfini gives partial credits for reasonable moves.

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- Results from my seminar show that difficulty goes with entropy more than previously expected.

9. Signal Consistency

Suppose we know an overall Elo skill level E for a set of players in advance. On (which) subsets of the data should we expect a metric μ to give consistent readings in the vicinity of E?

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- Reasonable on, say, positions with +1.00 or more advantage, versus positions with -1.00 or worse disadvantage, versus evenly balanced positions.

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I typically design exams to have about

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Should we use metrics that would say "A" even on the difficult questions by themselves, rather than rely on the exam being overall farly designed? Matters for *adaptive-difficulty* automated exams, which grade you by finding the level at which you score 50% (or 75% or etc). (IRT theory again).

Conclusions and Future Work

Q&A and Thanks

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- In a 500-player Open, **you should see ten such scores**.

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- **Now suppose the factual positivity rate is 20%.** Can we do this in our heads?

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- *Sensitivity and soundness generally remain separate criteria.*
- This is relevant insofar as I often get a lot of 3.00–4.00 range results.

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- With this patched, justified in saying the model paints chess moves on a 1,000-sided die and *simply rolls it*.

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- What I actually do is adjust σ up to σ'_E with dependence on Elo rating E determined by millions of **randomized resampling** trials from the training sets.
- With this patched, justified in saying the model paints chess moves on a 1,000-sided die and *simply rolls it.* $\implies$ multinomial Bernoulli trials.

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- Does not account for the *difficulty* of games. That is the job of the full model.

Z-Scores and Cheating Tests

For the aggregate quantities, the Central Limit Theorem in practice allows treating

$$z' = \frac{(\text{actual}) - (\text{predicted})}{\sigma'}$$

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- **Sensitivity**: Factual cheaters yield "high enough" z'.

From this point on, let's suppose my model has these properties. What about interpreting the results?

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Are these considerations orthogonal, or do they align?

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- Science, of course, demands criterion 1.

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- But reckon against time-scale of actual cases and tolerated error rate.

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- Chess.com "Titled Tuesdays" ...

The combination of the online 100-1 prior and marquee online events amps up the calculus.

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- Well, z-hacking/p-hacking is a huge area...

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Applying "Look-Elsewhere" still leaves astronomical confidence that *some* cheating occurred. Still leaves the question of who.

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- My formulas—"screening" as well as the predictive analytic model—scale as $O(\sqrt{n})$ gracefully to any sample size n of games/moves:
  - 5-game weekend tournaments;
  - 9-game international Opens;
  - 13-game invitational round-robins;
  - 12–24 game championship matches.
- But how about 300+ games played in "Titled Tuesdays" over a half-year span?
- Skew from rating estimation error scales *linearly* as $\Omega(n)$.
- Overflows the $O(\sqrt{n})$ levees... Validation by myriad resampling trials done on $n = 4, 9, 16$.

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- Basically running a more accurate rating system from the back of an envelope.

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- Reasonable *a-priori* since chess rating system is designed for additive invariance: only the difference in ratings to the opponent matters for predictions.

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- Does this make *time* fungible with *difficulty*, the latter as modeled by Item Response Theory?

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When is it important that our models include gravity?

Q & A

And Thanks.