Data Science Lessons From a Predictive Chess Model

Smith College Computer Science

Kenneth W. Regan[1]
University at Buffalo (SUNY)

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[1]With grateful acknowledgment to co-authors and UB's Center for Computational Research (CCR)

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In my model, the m_j are possible moves in chess positions.

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

- s for "sensitivity"—strategic judgment.
- c for "consistency" in surviving tactical minefields.
- h for "heave" or "Nudge"—obverse to depth of thinking.

Trained on all available in-person classical games in 2010–2019 between players within 10 Elo of a marker 1025, 1050, . . . , 275, 2800, 2825. Wider selection below 1500 and above 2500.

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The statistical application then follows by math known since the 1700s. (Example of "Explainable AI" at small cost in power.)

Validate the model on millions of randomized trials involving "Frankenstein Players" to ensure conformance to the standard bell curve at all rating levels.

See: Published papers and articles on Richard J. Lipton's blog **Gödel's Lost Letter and P=NP** which I partner.

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- Build not a Model but a Root System.

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

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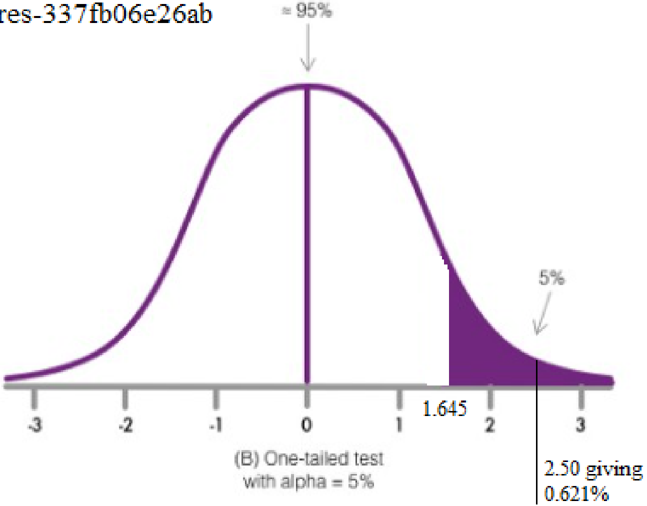
- Like with a **Richter Scale**, +1 matters a lot.

Bell Curve and Tails

From https://towardsdatascience.com/hypothesis-testing-z-scores-337fb06e26ab



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- The severe underfitting causes other problems for $N \gg 500$.

Demonstration

- At this point I showed data from the full model results, including from the recent European Individual Championships.
- The model is trained to make **MM%** (engine move-match) and **ASD** (scaled average centipawn loss) into **unbiased estimators**.
- Although the projections on the engine's second and third moves are moderately out of true, the 4th moves onward agree closely, while projections of various levels of mistakes are in fair agreement.
- In 10–15% of positions, the model projects an inferior move to be more likely than the engine's favored move. This yields 2–3 percentage points gain in predicting the played moves, compared to "betting the favorite" move. See this GLL blog article.
- *Advancing moves*, *capture moves*, and *moves with the knights* are played far more often than the model projects.
- Is it better to leave these human tendencies as "theorems" of the model in its minimalist form, or alter projections after-the-fact to match them?

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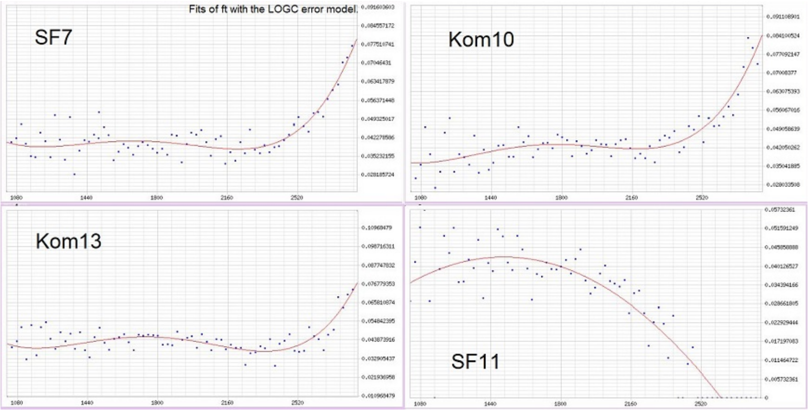

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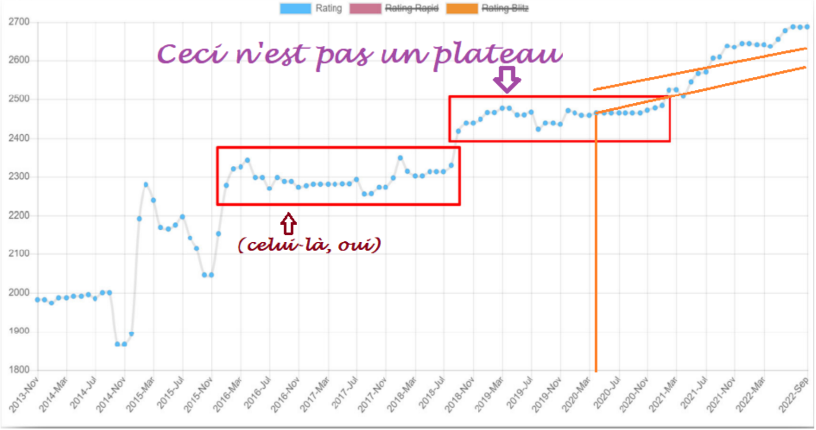
- Would have been more "normal" if comprehensive studies of the career arcs (measured by Elo rating) of young players were to hand.
- Lack of such studies exposed by the controversy over Hans Niemann's rise from 2465 Elo to 2700.

Hans Niemann: Platform or Plateau?



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- What data could corroborate a result—or a proposed explanation?

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Two more concluding points in the meantime:

1. I have accepted lower sensitivity and predictivity in order to preserve *explainability* and gain *robustness*. Neural methods have been brittle in ways discussed here and here. I present a recent instance linked in an Update at the bottom of this GLL blog post.
2. Models should promote multiple paths of engagement with reality.

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- Both determined and vetted by millions of *resampling* trials—emphasizing 4-game, 9-game, and 16-game sets.

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- Safe models can still give false positives in (*normally rare*) cases.

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- Interpret 100-1 to 1,000-1 as range of **comfortable satisfaction** per CAS Lausanne.

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- (This is really how a "second opinion" operates in practice.)
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- Still not **comfortable satisfaction** of the result being unnatural.
- IMPHO, the interpretation of CAS comfortable-satisfaction range of **final odds** determination is **99%–99.9%** confidence.
- Target confidence should depend on gravity of consequences. (CAS)
- Sweet spot IMHO is **99.5%**, meaning **1-in-200** ultimate chance of wrong decision. Same criterion used by **Decision Desk HQ** to "call" US elections.
- Higher stringency cuts against timely public service.

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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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- E.g., if both z_1 and z_2 are 3.5 then $z = \frac{7.0}{1.414...} \simeq 4.95$.
- Face-value odds about 1 in 2.7 million, enough for "any" prior.

Interpretations III: Other Distinguishing Marks

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- Far more likely that $z = 4$ means cheating. The false-positive guy under this combination won't arise in 60 years.
- Logic goes for $z = 3$ and $z = 2.75$ and even $z = 2.5$ (1-in-161 frequency).

But in situation (b), it matters *how many* players do it, and whether it is *neutral* or *material*.

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- So **30-to-1** odds against this year—especially if this is the first year of the policy.
- Not enough for comfortable satisfaction, but $z = 4.265$ gives 1-in-100, $z = 4.42$ gives 1-in-200 (round number $z = 4.5$).

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- If we have a catalogue of **10** things like this, we err once in **20** years.
- (As it happens, my sharper August 2019 model gave some $z > 5$ readings, then more games were found which made $z > 6$ overall.)