Statistical Chess Cheating Detection

Marshall Chess Club, with USCF and CFC

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

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- 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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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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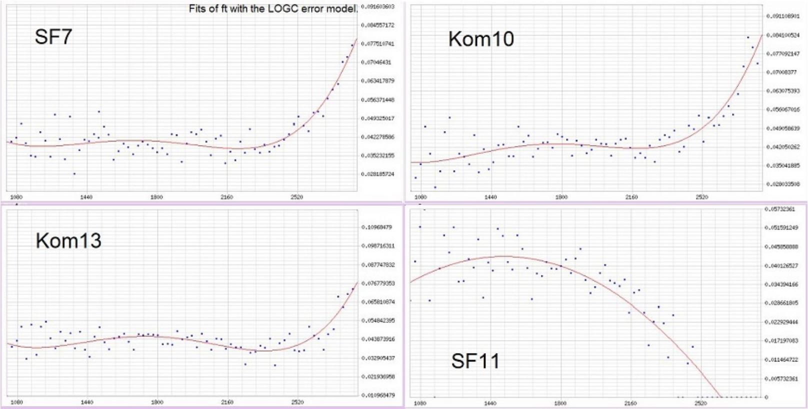

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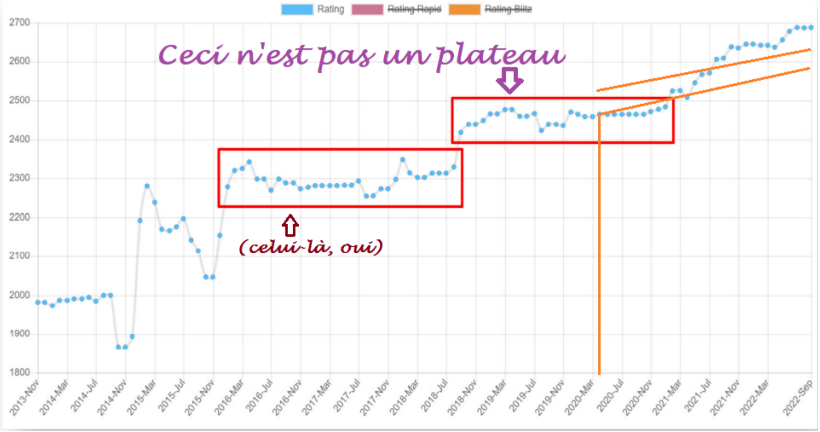
- Interpret 100-1 to 1,000-1 as range of **comfortable satisfaction** per CAS Lausanne.

Images de "Tricherie"? Graph eines Niemann

The #1 scientific role I've played during the pandemic has been estimating the true skill growth of young players while their official ratings have been frozen.



(The initial talk (10 minutes before Q&A) ended here...)

Two items of larger scientific significance:

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. I suspect that model designers often *satisfice*. That is, they design a model for one purpose but do not sufficiently explore the neighboring problem space for proof against "mission creep" or situational data bias, nor invest in cross-validation. I intend to criticize this study, whose results I do not reproduce.

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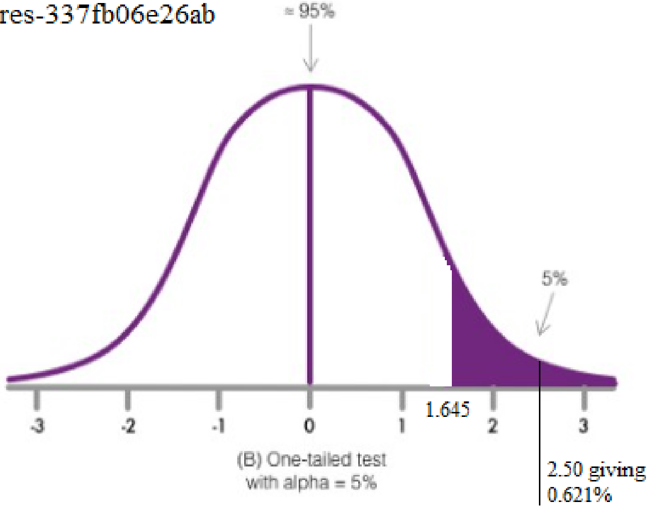
- Like with a **Richter Scale**, +1 matters a lot.

Bell Curve and Tails

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



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- For screening test, prefer $N = 100$ (usually 4 games).

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- **z = 5.00: 1-in-3,486,914** odds, 2.87/10,000,000 natural freq.
- But face-value odds need to be tempered against Bayesian priors, the look-elsewhere effect, and possible selection bias.

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

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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.

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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.)