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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- Addresses a series of events or decisions, each with possible outcomes $m_1, m_2, \ldots, m_j, \ldots$
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- Also assigns confidence intervals for $p_j$ and those quantities.

Mine is based on a utility function / loss function in a standard way except for being log-log linear, not log-linear. Has parameters

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- $s$ 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, \ldots, 275, 2800, 2825. Wider selection below 1500 and above 2500.
How it Works

Take $s, c, h$ from a player's rating (or "profile"). Generate probability $p_i$ for each legal move $m_i$. Paint $m_i$ on a 1,000-sided die, 1,000 $p_i$ times. Roll the die. (Correct after-the-fact for chess decisions not being independent.)

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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How Well Does It Work?

Internal evidence that it gives \((1 + \epsilon)\) relative error with \(\epsilon \approx 0.04\) for most rating levels.
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Example Application and Reasoning

Suppose one gets a $z$-score of $4.00$. 

The primary meaning is that the performance has a natural frequency of about $1$-in-$31,574$, for that quality or higher.

Let’s round that to what I call “Face-Value Odds” of $30,000$-to-$1$.

This needs to be rectified according to various factors:

- The prior likelihood of cheating.
  - In-person: $1$-in-$5,000$ to $1$-in-$10,000$?
  - Online: $1$-in-$50$ to $1$-in-$100$.

- The look-elsewhere effect: How many others could you have tested? How many in the tournament? How many others playing comparable-level chess that weekend? week? month? year?

Presence of other, non-quality evidence offsets these matters.

OTB, divide $30,000$ by $10,000$ leaves just a “balance of probability.” Insufficient. Need $z \geq 5$ for comfort.

Online, dividing by $100$ leaves $300$-to-$1$ “reckoned odds” against the null hypothesis of fair play.

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

For **independent** situations whose results add up, one can replace probabilities by **Z-scores**, which quantify deviations of averages from expected means.

- Like how raw numbers are indexed by their logarithms on a slide rule.

\[ z = \frac{X - \mu}{\sigma} \]

Where:
- \( z \) is the Z-score.
- \( X \) is the raw score.
- \( \mu \) is the mean of the distribution.
- \( \sigma \) is the standard deviation of the distribution.

For example, \( z = 2 \) indexes the probability that 15 or more homes get flooded, about 1-in-44, which is somewhat under 2.5% probability.

\[ z = 3 \] means at least "17.5" homes being flooded, 1-in-741 frequency.

\[ z = 4 \] means 20 or more flooded, for 1-in-31,575 frequency.

(Ignoring that "half a home" matters here too.)

\[ z = 6 \] means 25 or more. A "Six-Sigma Deviation": 1-in-a-billion.

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Bell Curve and Tails

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

(B) One-tailed test with alpha = 5%

2.50 giving 0.621%
Central Limit Theorem and “Rule of 30”

**Theorem (CLT)**

*For any probability distribution $D$, the mean of $N$ independent samples from $D$ is distributed more like the bell curve as $N \to \infty$.***
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For any probability distribution $D$, the mean of $N$ independent samples from $D$ is distributed more like the bell curve as $N \rightarrow \infty$.

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- But it stays “chessy.” I’m fully comfortable with $N = 50$.
- For screening test, prefer $N = 100$ (usually 4 games).
Using Z-Scores

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- The common “sigma” units allow combining z-scores of disparate events.

\[
\begin{align*}
\text{z} = 2.00 & : \text{1-in-44 odds, 2.275\% natural frequency.} \\
\text{z} = 3.00 & : \text{1-in-741 odds, 0.135\% natural frequency.} \\
\text{z} = 4.00 & : \text{1-in-31,574 odds, 3.167/100,000 natural freq.} \\
\text{z} = 5.00 & : \text{1-in-3,486,914 odds, 2.87/10,000,000 natural freq.}
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\]

But face-value odds need to be tempered against Bayesian priors, the look-elsewhere effect, and possible selection bias.
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- Both determined and vetted by millions of resampling trials—emphasizing 4-game, 9-game, and 16-game sets.
Sensitivity, Soundness, and Safety

Model is sensitive if whenever there is a high deviation in fact, the model registers a high $z$-score. Also termed: the model avoids false negatives / avoids type-2 errors.

Model is sound if whenever it measures a high $z$-score there is a factual high deviation. Aka.: avoids false positives / avoids type-1 errors.

Model is safe if in the absence of systematic deviations, the $z$-scores it gives follow a normal distribution — or at least are conservatively within the $z \geq 2$ high end of the standard bell curve.

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Statistical Chess Cheating Detection

Interpreting Results I.

Suppose we get $z = 4$. Natural frequency is 1-in-31,574. Can we conclude 31,573-to-1 odds that the result is unnatural (i.e., cheating)? Not so fast. Interpretation needs Bayesian reasoning about the prior rate of cheating. If no one could possibly be cheating, it must have been a rare but natural event. If several cheaters have already been found, chances are you caught another. If this is an anomaly in a 500-player Open, hmm... Context Matters, unfortunately... or fortunately—even in quantum mechanics, the basic working of Nature. Or at least in population medicine...
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Consider giving the test to 5,000 people, including yourself. Among them, 1 has the cancer; expect that result to be positive. But we can also expect about 100 false positives. All you know at this point is: you are one of 101 positives. So the odds are still 100-1 against your having the cancer. The test result knocked down your prior 5,000-to-1 odds-against by a factor of 50, but not all the way. Need a "Second Opinion." IMPHO, 1-in-5,000 ≈ frequency of cheating in-person.

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Suppose our cancer test were 600 times more accurate: 1-in-30,000 error. That's the face-value error rate claimed by a \( z = 4 \) result. Still 1-in-6 chance of false positive among 5,000 people. (This is really how a "second opinion" operates in practice.) If the entire world were a 500-player Open, then 1-in-60 chance of the result being natural. 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 IMPHO 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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The 99.993% Test

- Suppose our cancer test were 600 times more accurate: 1-in-30,000 error.
- That’s the face-value error rate claimed by a $z = 4$ result.
- Still 1-in-6 chance of false positive among 5,000 people.
- (This is really how a “second opinion” operates in practice.)
- If the entire world were a 500-player Open, then 1-in-60 chance of the result being natural.
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- Higher stringency cuts against timely public service.
Now suppose the factual positivity rate is 1-in-50. We still have about 100 false positives, but now also 100 factual positives. A positive from a 98% test is here a 50-50 coinflip. But a negative is good: Only 2 false negatives will expect to come from the 100 dangerous people. From the 4,900 safe people, about 4,800 true negatives. Odds that your negative is false are 2,400-to-1 against. Fine to be on a plane. What happened is that the 98%-test result multiplied your confidence in not having Covid by a factor of almost 50.

Now suppose the factual positivity rate is 20%. Can we do this in our heads?
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Covid in Non-Surge and Surge Times

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Suppose we get $z = 4$ in online chess with adult cheating rate 2%. Out of 30,000 people:

- 1 false positive result.
- 600 factual positives.

So $600 - 1$ odds against the null hypothesis on the $z = 4$ person. A $z = 3.75$ threshold leaves about $200 - 1$ odds.

OK here, but not if factual rate is under 1%. This analysis does not depend on how many of the factual positives gave positive test results.

If test is only 10% sensitive, then we will have only about 60 positive results. It sounds like the 1-in-60 case. But the chance of getting a $z = 4$ result on the 1 brilliant player also generally goes down to 1-in-10. The confidence ratio is $60 / 0.1 = 600$-to-1 even so.

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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Interpretations II: Multiple Factors

Online platforms collect data on player behavior: clicks, changes in window focus, timing of moves. Independence is relative to profiled tendencies. For repeated actions, CLT applies, so deviations can be expressed via $z$-scores. If you get $z_1$ from quality metrics and $z_2$ from the interface ("telemetry"), weight these factors equally, and consider them independent, then the overall $z$-score is

$$z = z_1 + z_2 \sqrt{2}.$$ 

(E.g., if both $z_1$ and $z_2$ are 3.5 then $z_1 = 7$.0.414... $\approx 4.95$. Face-value odds about 1 in 2.7 million, enough for "any" prior.)
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Suppose we have one of these two situations with player giving $z = 4$:

(a) Player found with cellphone on person.
(b) Player stowed cellphone in bag under chair, switched off [but it still rang].

In (a), there do not exist 31,574 or even 500 players who do this normally (in any year). Can sanction for violation of rule in any event. 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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If (b) is also material (or otherwise "covariant") with cheating, then I argue the face-value odds from the $z$-score become true odds, same as in situation (a).

Even if (b) is neutral, still a problem if: the behavior is infrequent, and we are not keeping a large catalogue of arbitrary/impertinent behaviors.

Suppose only 1,000 players do (b) in any year. Then the false-positive guy for $z = 4 \land (b)$ comes only once per 31.5 years. So 30-to-1 odds against this year—especially if this is the first year of the policy. Not enough for comfortable satisfaction, but $z = 4\cdot.265$ gives 1-in-100, $z = 4\cdot.42$ gives 1-in-200 (round number $z = 4\cdot.5$).
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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.)