Data Science Lessons From a Predictive Chess Model
Smith College Computer Science

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\textsuperscript{1}With grateful acknowledgment to co-authors and UB’s Center for Computational Research (CCR)
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Example: An insurance company may estimate that:

The probability of a given house having flood damage in a 5-year period is 10% with "95%" confidence that it's between 5% and 15%.

This means that out of 100 homes in similar and independent locations, they expect 10 to be flooded, with 95% confidence of no better than 5 but no worse than 15.

Homes being close together does not affect the expectation but does widen the confidence interval.

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In my model, the \( m_j \) are possible moves in chess positions.
The model is based on a utility function / loss function in a standard way—except for being log-log linear, not log-linear (why). The (dis-)utility comes from (my heavily scaled version of) average centipawn loss of the played move compared to (what a powerful chess-playing program thinks is) the best move. No chess knowledge other than the move values is input.

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

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Despite being severely underfitted, the model works checkably well.

Many deployed models satisfice—designed toward one prime objective but don't build in cross-checks or invest in the space of neighboring objectives.

Nonreproducibility, Mission Creep, and Shifting Sands.

E.g., I do not reproduce the longer conclusions of this study.

Going back to my model, since it is fundamentally incorrect regarding independence, the cross-checks are a vital basis.

Build not a Model but a Root System.
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Build not a Model but a Root System.
Pre-Check: The “Screening” Stage

Makes a simple “box score” of agreements to the chess engine being tested and the scaled average centipawn loss from disagreements. Creates a Raw Outlier Index (ROI) on the same 0-100 scale as flipping a fair coin 100 times. Here 50 is the expectation given one’s rating and 5 is the standard deviation, so the “two-sigma normal range” is 40-to-60. Like medical stats except indexed to common normal scale. 65 = amber alert, 70 = code orange, 75 = red. Example. Completely data driven.

Rapid and Blitz trained on in-person events in 2019. Slow chess trained on in-person FIDE Olympiads from 2010 to 2018. Example: The just-finished European Individual CC. Does not account for the difficulty of games. That is the job of the full model.
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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.

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

A **z-value** denotes the natural frequency of at least \( yea-much \) deviation. In our homes and flooding 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. Like with a **Richter Scale**, +1 matters a lot.
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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”

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In chess, the distribution $D$ isn’t the same for different chess positions. But it stays “chessy.” I’m fully comfortable with $N = 50$.

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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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Data Science Lessons From a Predictive Chess Model

Hans Niemann: Platform or Plateau?

*Ceci n’est pas un plateau*

*(celui-là, oui)*
Is clear: with Judit Polgar retired, there are no women in the top 100 by rating.

Where/when does it begin?

How should one begin to address this question?

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.
Using Z-Scores

- Golf-shot analogy for why one uses the whole tail.
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- The common “sigma” units allow combining z-scores of disparate events.

The z-value gives “Face-Value odds” against the null hypothesis of the deviation occurring by natural chance.

- $z = 2.00$: 1-in-44 odds, 2.275% natural frequency.
- $z = 3.00$: 1-in-741 odds, 0.135% natural frequency.
- $z = 4.00$: 1-in-31,574 odds, 3.167/100,000 natural freq.
- $z = 5.00$: 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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- These are my **adjusted z-scores**.
- 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.

It is possible for models to be safe without being sensitive. My model has preserved safety while improving sensitivity. Safe models can still give false positives in (normally rare) cases.
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Suppose one gets a $z$-score of $4.00$. 
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- 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.

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Cancer and Covid (= in-person and online chess)

Say you take a test that is 98% accurate for a cancer that affects 1-in-5,000 people...

...and get a positive. What are the odds that you have the cancer? Not the same as the odds that any one test result is wrong.

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. A positive from a "98%" test is like getting z = 2.05. Not enough.

In a 500-player Open, you should see ten such scores.
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- Not the same as the odds that any one test result is wrong.
- 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.
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- In a 500-player Open, you should see ten such scores.
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. 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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Suppose we get $z = 4$ in online chess with adult cheating rate 2%. Out of 30,000 people:

- 1 false positive result.
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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 generally goes down to 1-in-10. The confidence ratio is $60/0 = 600$-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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This is relevant insofar as I often get a lot of 3.00–4.00 range results.
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 $z = z_1 + z_2 \sqrt{2}$.

(If you give weights $w_1, w_2$ then the formula is $z = w_1 z_1 + w_2 z_2 \sqrt{w_1^2 + w_2^2}$.)

E.g., if both $z_1$ and $z_2$ are 3.5 then $z = 7.0414... \approx 4.95$. Face-value odds about 1 in 2.7 million, enough for "any" prior.
Interpretations II: Multiple Factors

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(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 $z = 2$.

But in situation (b), it matters how many players do it, and whether it is neutral or material.
Interpretations III: Other Distinguishing Marks

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- 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.
Distinguishing Marks, continued

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 $z = 4.265$ 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.)