Cheating Detection and Cognitive Modeling at Chess
CS Distinguished Lecture, Northwestern University

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¹With grateful acknowledgment to co-authors Guy Haworth and Tamal Biswas, students in my graduate seminars, and UB’s Center for Computational Research (CCR)
A Simple Utility-Based Model

Utility \equiv\text{values given by strong chess-playing programs (called "engines") to possible move choices in a series of chess positions in games by a player (or aggregate of players). In familiar units of pawns or \((x \times 100)\) centipawns. E.g. +1.50 means the player to move is figuratively a pawn and a half (\(= 150\) cp) ahead. Alternative: as probabilities of winning/drawing (say \(p_{\text{win}} + 0.5 p_{\text{draw}}\)). The model knows nothing else* about chess. No pieces, no board geometry. Only other ingredients: player skill parameters \(s,c,e,v\) (plus hyperparameters) and their correspondence to Elo chess ratings. (*The model does track how the calculated values of moves change as the engine progresses through depths of search.)
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Elo Chess Ratings—and Why Cheat?

- Named for Arpad Elo, number \( R_P \) rates skill of player \( P \).

\[
p = \frac{1}{1 + e^{-c \Delta}}
\]

where \( \Delta = R_P - R_O \) is the difference to your opponent’s rating.

Taking \( c = (\ln 10)/400 \) makes \( \Delta = 200 \) give about 75% expectation.

Class Units: 2000–2200 = Expert, 2200–2400 = Master, 2400–2600 is typical of International/Senior Master and Grandmaster ranks, 2600–2800 = “Super GM,”; Carlsen only player over 2800.

Adult beginner \( \approx 600 \), kids \( \rightarrow 100 \).

Stockfish 16 3544, Torch 1.0 3531, Komodo Dragon 3.3 3529.

So computers are at “Class 15.”

\( \Rightarrow \) a “Moore’s Law of Games.”

Other Q: How do computer evaluations translate to chances of winning?
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Move Utilities Example (Kramnik-Anand, 2008)
Utility-Based Predictive Modeling

Predictive modeling gives probabilities $p_i$ for each option/event $m_i$. The relation to utility is usually log-linear:

$$\log(p_i) = \alpha + \beta u_i.$$ 

Equivalently, if we rank options by best-first utility:

$$\log(p_1) - \log(p_i) = \beta (u_1 - u_i) \equiv \beta \delta_i.$$ 

Solved via softmax:

$$p_i = \frac{\exp(\beta \delta_i)}{\sum_{\ell=1}^{\ell} \exp(\beta \delta_{\ell})}.$$ 

With $\delta_1 = 0$, so that $\exp(\beta \delta_1) = 1$, this gives $p_1 = 1/\sum_{\ell} p_{\ell}$ and $p_i = p_1 \exp(-\beta \delta_i)$ if you keep $\beta$ positive. Probabilities are multiples of $p_1$. 
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Loglog-Linear Model

\[ \log \log \left( \frac{1}{p_i} \right) - \log \log \left( \frac{1}{p_1} \right) = \beta \delta_i. \]

Equivalently,

\[ \frac{\log(1/p_i)}{\log(1/p_1)} = r_i = \exp(\beta \delta_i). \]
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A rare bird? Relation to power-law phenomena?
Parameters and Nonlinearity

Note $\beta$ cancels the centipawn units of $\delta_i$, so we write $\delta_i$ instead. Since $\delta_i$ is dimensionless, can raise to any power $c$.

Basic log-linear model becomes:

$$p_i = p_1 \cdot \exp(-\left(\delta_i\right)^c).$$

Double-log model becomes:

$$p_i = p \exp\left(\left(\delta_i\right)^c\right).$$

Intuition either way: Lower (=better) sensitivity magnifies effect of small $\delta_i$, $\Rightarrow$ better strategic ability to perceive small advantages. Like Anatoly Karpov. Higher (=better) consistency drives down $p_i$ for moves of large $\delta_i$, ability to survive tactical minefields. Like Mikhail Tal.
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Karpov & Tal at Montreal “Tourney of Stars” 1979
Tied for first with 12/18 in star-studded double round-robin.
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- Karpov (per SF11): \( s = 0.01558, c = 0.30702 \).

Trained correspondence to Elo rating gives Karpov **2625 \( \pm \) 155**, Tal **2730 \( \pm \) 185**.

These are my **Intrinsic Performance Ratings (IPRs)**.

Whole tourney IPR is (only!) **2575 \( \pm \) 50**.

(With \( s = 0.04121, c = 0.38525 \).)

Average Elo of players, **2621**, is within error bars.

Surprise is that the IPR is not near 2700s range.
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Whole tourney IPR is (only!) 2575 $\pm$ 50. (With $s = 0.04121$, $c = 0.38525$.)
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- Karpov was rated 2705, Tal only 2615.
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Test Quantities and Parameter Fitting

Over $T$-many game turns $t$ by a player (or players), solve to make the following two test quantities into **unbiased estimators**: 

$T_1 - \text{Match}$: Make the actual number $t_1$ of agreements with the engine equal to $t_1^\text{proj} = \sum_{t=1}^{T} p_{1,t}$. 

$\text{ASD}$: Make the scaled “average centipawn loss” $\text{asd}$ of a player’s moves $m_i t, t$—as judged by the testing engine—equal to $\text{asd}^\text{proj} = \sum_{t=1}^{T} \sum_{i=1}^{\ell} p_{i,t} \delta_{i,t}$. 

Alternative fitting methods include maximum-likelihood estimation, equivalently, minimizing $\sum_{t=1}^{T} \log \left( \frac{1}{p_{it,t}} \right)$. 
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Other Quantities of Interest

EV-Match: About 8–10% of positions have multiple optimal moves. Include them all as a "match."

T2-Match: Include the second-best move as a "match."

(T2-Match is a blunder.)

M2: p2,t vs. actual frequency of playing second-best move.

T3, M3, etc.: "T3-match" much-discussed cheating metric.

Error100: Mistakes mi with δi ≥ 100 (i.e., one pawn).

Error200: Moves mi with δi ≥ 200, "game-losing blunders."

Delta(u,v): moves with u ≤ δi ≤ v, "small slips."

Captures, advancing vs. retreating moves, moves with Knights or other specific pieces...
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Original Idea (2015–2017): Add a term $\rho_i$ for “perceived” (change in) value over lower depths of search. Higher for “trappy” moves. Multiply by third parameter $h$:

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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* \( \mathbf{M}_2 \) and \( \mathbf{M}_3 \), the fitted double-log model underestimates them (hence also \( \mathbf{T}_2 \) and \( \mathbf{T}_3 \)) only slightly. Moreover:

For each other metric \( \mu \), 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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(Voiceover: They’re not.)

But it is a sparse, nearest-neighbor dependence, hence approximable by scalar means without having to model big covariance matrices. Gets done empirically via said resampling trials.

That ensures safety (against false positives).

How about sensitivity (avoiding false negatives)?
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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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"Solitaire Chess" feature often gives part credits. Large field of Item Response Theory (IRT).
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Relationship of Quality to Thinking Time Budget. (show graph)
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Cheating Detection and Cognitive Modeling at Chess

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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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- Predicated on making their move within **5 seconds** they played...**well over 3000 level**.
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- If we include having little time left into the predicate—average before turn 40 or overall—then results are closer to expectation.
- (From my recent graduate seminar. Q&A phase can begin here.)
8. How to Measure “Difficulty”? 

Does it equal “Hazard”—meaning the expected loss of value (and of win/draw probability) from the choice of move? Or does it have more to do with the chance of finding an optimal move?

Correspondence to Multiple-Choice Tests. 

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Entropy and Difficulty

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Results from my seminar show that difficulty goes with entropy more than previously expected.
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 $\mu$ to give consistent readings in the vicinity of $E$?
9. Signal Consistency

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- ASD metric—?
- IPR metric—?? By intent, this *should* give signal consistency.
- Reasonable on, say, positions with $+1.00$ or more advantage, versus positions with $-1.00$ or worse disadvantage, versus evenly balanced positions.
Examination Grading Analogy

I typically design exams to have about
- 20% A-level questions (and points)
- 30% B-level,
- 30% C-level, and
- 20% D-level, with 90% the target for an A grade.

Means that getting 60% on the A-level questions is reasonably on-track for an A, even though 60% by itself is a “C signal.”
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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 fairly 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
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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That's the face-value error rate claimed by a $z = 4$ result.
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(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 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 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.
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Now suppose the factual positivity rate is 20%. Can we do this in our heads?
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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Back to Chess...

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- They're not. But it's a sparse dependence on neighboring moves. (Not across games—common "opening book" is removed from the sample.) 

  - Covariance matrix is banded, hence approximable by scalars. 
  
  - Could treat as a "reduced-entropy" sample size $T' < T$. 
  
  - What I actually do is adjust $\sigma$ up to $\sigma'$ with dependence on Elo rating $E$ determined by millions of randomized resampling trials from the training sets. 

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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.

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

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- **Sensitivity**: Factual cheaters yield “high enough” \( z' \).

\textit{From this point on, let’s suppose my model has these properties. What about interpreting the results?}
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Look-Elsewhere Effect: How many were playing chess that day? Weekend? Month? Year? Are these considerations orthogonal, or do they align?
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I interpret the range of comfortable satisfaction as 99–99.9% final confidence. For calling elections, Decision Desk HQ uses 99.5% confidence. Not quite right to say 1-in-200 error, i.e. a "Florida" every 4 cycles, because returns often blast past that instantly. So maybe truer chess analogue is 1-in-500 error. Judge by "Countenanced Error Rate Per Year." E.g. if 10 cases per year reach judgment stage, and you can tolerate 1 error per 20 years, then 99.5... But online chess has 10,000+ cases per year...
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Approximately 100,000 players-in-event per year among “notable” events. Notable ≡ some or all gamescores preserved. A highly computerlike game is a “shiny marble”—players do notice. Accounted over a year, suggests to divide odds by 100,000. 4.75 sigma → only 90% confidence. 5.00 sigma → 1-in-35 error. Sounds like 1-in-35 error is still too high based on confidence target. But reckon against time-scale of actual cases and tolerated error rate.
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- Key point: What are the odds of getting this once-in-50-years event **this (early) year?**

(My formal IP agreement with FIDE is 20 months old.)

(But I deployed my model in 2011.)

Better argument?: Balance against the arrival rate of real cases. Aligns with Bayesian prior on average, but should allow for variance in the rate. Figure discount by 25,000 to 50,000. Then 5-sigma is OK.
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- (But I deployed my model in 2011.)

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- Aligns with Bayesian prior on average, but should allow for variance in the rate.
Doomsday to the Rescue?

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Issue #4: Event Tiers

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- The Carlsen Online Chess Tour.
- Chess.com “Titled Tuesdays” ...

The combination of the online 100-1 prior and marquee online events amps up the calculus.
Issue #5: Distinguishing Marks

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- Yet another separate matter from the Bayesian prior.
Super-Fraught Issue #6: Multi-Testing Samples

What if a player seems to have cheated only in games 5–8 of a nine-game Open? Or maybe games 4–6 and 8–9? Proper domain of Bonferroni Correction if it doesn't wipe out significance altogether. Well, \( z \)-hacking/p-hacking is a huge area...
Super-Fraught Issue #6: Multi-Testing Samples

- Includes Cherry-Picking and other forms of $p$-hacking.
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What if you get $z = 3.54$ on three different players in a 500-player Open? Not enough to convict any one player. But odds against all being fair can be estimated by aggregating $z$-scores, presuming (under the null hypothesis of fair play) that the players' actions are independent:

$$z = z_1 + z_2 + z_3 \approx 6.13$$

Billion-to-one

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Issue #8: Scaling of Estimation Error
Cheating Detection and Cognitive Modeling at Chess

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Issue #9: Biased Inputs

Lag in ratings of rapidly improving young players. Was exponentiated by the pandemic. "Pandemic Lag" article on the GLL blog. Cause of many unwarranted suspicions, even recently. Also geographical variations in ratings. As in issue 8, rating estimation bias skews linearly. My model has enough cross-checks to detect and correct the bias—mainly need only assume not everyone is cheating. No "interstellar dust" issue.
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Arguments over the Niemann-Carlsen fracas a year ago exposed the lack of any rigorous studies of the growth curves of young improving players. In Sept.-Nov. 2020, I fitted a simple formula from observations of players in multi-age youth events 5–7 months since their official ratings were frozen. I am still using fairly much the same formula, now 43 months in. Well, with some tweaks: Reduced multiplier for players under age 12 from 30 Elo per month to 25; later filled in 20x for ages 12 and 13 as of April 2020.

Gains above Elo 2000 reduced by treating formula as a differential. Gain estimations reduced for females age 12 and up. Formula for teenagers (with 15 multiplier) otherwise unchanged.

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Post-Normal II: Time Dependence

The pandemic drove major tournaments online—where chess is played faster. Not enough reliable training data for (in-person) fast chess across skill levels. Panoply of different speeds anyway: \( \tau \) = time you can use to play. FIDE standard slow chess gives \( \tau = 150 \) minutes. Postulate: Elo reduction \( R(\tau) \) if largely independent of the player's Elo rating \( E \). 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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Reasonable *a-priori* since chess rating system is designed for additive invariance: only the difference in ratings to the opponent matters for predictions.
Reliable data for $\tau = 25$ and $\tau = 5$ (as well as $\tau \geq 150$) from the elite annual World Rapid and Blitz Championships. Guess that $R(\tau)$ is logistic in $\log \tau$, so polynomial rational in $\tau$. Gives four unknowns to fit, but only three equations. Try getting fourth from: Rating estimate of $\tau = 0$, i.e., of completely random chess. Implicitly done here. Aitken Extrapolation. Lo and behold—the two methods agree! Is the resulting "Rating Time Curve" thereby a natural law? Does this make time fungible with difficulty, the latter as modeled by Item Response Theory?
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Stance on Data Science

Concern: Data modelers in less-extreme settings satisfice. That is, their models are designed up to one particular goal but don’t explore much of the harder adjacent metaspace.

Nonreproducibility, Mission Creep, and Shifting Sands. E.g., I do not reproduce the longer conclusions of this study.

Here is a way of phrasing the question that comes from this stance: When is it important that our models include gravity?
Stance on Data Science

- Extreme Corner of Data Science—since I need ultra-high confidence on any claim.
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Q & A

And Thanks.