Time and Difficulty
Artificial Intelligence and Sustainable Computing (AISC 2024)

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13 July, 2024

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 Predictive Analytic Model

Means that the model:

- Addresses a series of events or decisions, each with possible outcomes $m_1, m_2, \ldots, m_j, \ldots$
- Assigns to each $m_j$ a probability $p_j$.
- Projects risk/reward quantities associated to the outcomes.
- Also assigns confidence intervals for $p_j$ and those quantities.

In a utility-based model, each $m_i$ has a utility or cost $u_i$. The main risk/reward quantity is then $E = \sum_i p_i u_i$. Examples:

- **Insurance**: $m_i$ are risk factors; costs $u_i$ do not influence $p_i$.
- **Chess**: $m_i$ are legal moves; $u_i$ are values given by strong chess-playing programs that objectively say how good the moves are. In my model, $p_i$ depend on $u_i$ per bounded rationality.
- **Multiple-choice tests**: $m_i$ are possible answers to a test question, $u_i = \text{gain/loss for right/wrong answer}$.
The ___ of drug-resistant strains of bacteria and viruses has ___ researchers’ hopes that permanent victories against many diseases have been achieved.

- **a** vigor . . corroborated
- **b** feebleness . . dashed
- **c** proliferation . . blighted
- **d** destruction . . disputed
- **e** disappearance . . frustrated

(source: itunes.apple.com)

Here (b,c) are **equal-optimal** choices, (a) is bad, but (d) and (e) are reasonable—worth part credit.
A Difficult Trap (Kramnik-Anand, 2008 WC)
Aptitude—Via Elo Grades (calculator)

- Named for **Arpad Elo**, number $R_P$ rates skill of player $P$.
- E.g. **1000** = bright beginner, **1600** = good club player, **2200** = master, **2800** = world championship caliber.
- Computer engines are far higher, e.g.: **Stockfish 16 = 3544**, **Torch 1.0 = 3531**, **Komodo Dragon 3.3 = 3529**.
- Expectation $e = \frac{1}{1 + \exp(c(R_P - R_O))}$ depends only on difference to opponent’s rating $R_O$. With $c = (\ln 10)/400$ the curve is:

![](chart.png)
Similar \textbf{0.75} expectation when up 1.30 vs. equal-rated player.

Complication: dependence on rating itself.
Item-Response Theory (IRT source)

- Horizontal axis governs difficulty in relation to $\theta = \text{ability}$.
- Slope at $y = 0.5$ correctness rate is the discrimination factor.
Defining Difficulty

For any fixed aptitude level \( \theta \), difficulty \( \approx \) expected points loss.

In chess, this is our \( EL = \sum_i p_i(u_1 - u_i) = \sum_i p_i \delta_i \).

Call this expected loss the **hazard**.

Depends on rating because the probabilities \( p_i \) projected by my model depend on rating \( R \).

My model divides out dependence on \( R \). “Expectation Weights, Normalized” (EWN).

**Technotes:** In a **log-linear** model, \( -\log p_i \sim u_i \).

Then \( EL \sim \sum_i p_i \log(1/p_1) - \sum_i p_i \log(1/p_i) = \log(\frac{1}{p_1}) - H \) where \( H \) is entropy.

**However**, my model is **double-log linear**: \( \frac{\log p_i}{\log p_1} \sim \exp(\delta_i) \).

Why double-log works and single-log fails.

How well does hazard—normalized over aptitude—work as a measure of difficulty?
A Philosophical Issue

Should a grading metric $\mu$ expect to assess lower performance on more-difficult questions, or should it show a constancy of signal $\theta$ across all types of questions?

- I typically design exams to have 20% A-level questions, 30% B-level, 30% C-level, 20% D-level.
- Overall threshold for A: 90%.
- Getting 60% on the A-level questions puts you on-track, even though 60% by itself is C-range (or worse).
- Thus the simple grading score $\mu$ does not give constant signal—it needs context.
- Should we use metrics that say “A-level” etc. in each category? (Like curving).
The following “raw metrics” on series of games are used generally:

- **T1-match**: Agreement with the move listed first by the computer.
- **EV-match**: Includes moves of equal-optimal value not listed first.
- **ASD**: Average difference in value from inferior moves (over all positions), but *scaled* down when one side has advantage.
  - Called **ACPL** for *average centipawn loss* without scaling.

All should vary with difficulty, hence not give constancy of signal.

- **My Intrinsic Performance Rating (IPR)** metric fits parameters
  - *s* for “sensitivity” (∼ strategic ability), and
  - *c* for “consistency” (in surviving tactical minefields)
  
  to give the closest *Virtual Player* $P(s, c)$ on any set of games.

Then trained correspondence $(s, c) \rightarrow R$ gives IPR as an Elo rating.

- Should give constancy of signal...but...
How Accurate Are Model Projections?

Internal evidence that it gives \( \approx (1 + \epsilon) \) relative error with \( \epsilon \approx 0.04 \) for most rating levels. Means it supports betting on chess moves with only 5% “vig” to avoid arbitrage. (Except for bets against clear-best moves.)
Older players, established ratings (but deflated), average 2080.


IPR overall: 2125 +- 40. Broken down according to [dis-]advantage:
  1–2 pawns behind: 2170 +- 105; worse: 2065 +- 110.
  1–2 pawns ahead: 2085 +- 120; better: 2020 +- 155
  Within 1.00 of equal: 2145 +- 45; within 0.50: 2125 +- 65.

Reasonable constancy of signal.

But on positions with $\geq 1.5$ times normal hazard: 2255 +- 65.

With $\geq 2x$ hazard: 2170 +- 115. Could be consistent. But—

Positions of of $0.5x$ or lower hazard: 1800 +- 180.

Not constancy of signal.

Low-hazard positions either have an obvious best move or many good moves.
Low-hazard because crisis is far off, but difficult in real chess terms. Low $E_L$, high entropy $H$. (Niemann lost.)
Aspects of Difficulty (Besides Hazard)

1. Needing deep cogitation to find best move or avoid a trap. *Expressly modeled*—e.g. to project the trap for Kramnik.

2. **Being at a disadvantage.** Chess, *not so much examinations.* Model performs fine.

3. **Humans perform poorly.** Basic with *repeatable* test questions. Repeatable chess positions, however, are *opening book knowledge.*

4. **Humans take a long time to answer.**
   - Can’t *project ahead of time* (owing to non-book ≡ non-repeatable).
   - But certainly directly captures the human *experience* of difficulty.

5. **Question is inherently complex or taxing.**
   - How to measure this internally?
   - Sunde, Zegners, and Strittmatter [*SZS, Jan. 2022*] propose counting the time (i.e., number of position nodes) needed by chwess engine to complete analysis to depth (say) 24.
   - Carow and Witzig [*CW, Feb. 2024*] consider all the above, but strive for human-chess based measures.
Time and Difficulty

Time Budget and Effect on Quality

- **FIDE Standard Time Control**: 90 minutes to turn 40, then 30 minutes more, with 30-second *increment* after every move. Allows 150 minutes to turn 60.

- “Standard” control must allow at least 120 minutes to turn 60.

- Some elite events allow 180, 195, even 210 minutes (to turn 60).

- **Rapid** means any time giving under 60 minutes and at least 10. Common is 15 min. plus 10-second increment, giving 25 to turn 60.

- **Blitz** means under 10 minutes, most common is 3 minutes + 2-second increment, which gives 5 minutes—and so approximates old-school 5-minute chess on analog clocks.

- For 25-minute Rapid, I measure 240 reduction in quality per IPR.

- For 5-minute Blitz, 575 lower. (Error bars for both are about ±25.)
Time-Quality Curves (whole graph)
Time and Difficulty

Predicated on Time Spent For a Move

Staying with players rated 2000 to 2200 at the World Senior Team Ch.

- Positions on which they spent at most 30 seconds on the move: \( 2860 \pm 75 \).
- At most 10 seconds: \( 3235 \pm 90 \).
- Starting at turn 16 rather than 9: \( 3220 \pm 100 \).
- At most 5 seconds (sample size 605): \( 3230 \pm 160 \).

What gives here? How about moves with long thinks—?

- Positions with 5–10 minutes consumed: \( 1460 \pm 85 \).
- Using 10–15 minutes (705 positions): \( 1235 \pm 170 \).
- Using \( \geq 15 \) minutes (371 positions): \( 1410 \pm 205 \).
- “Thinking Is Bad For You.” (At least it’s a bad sign...)
- Vivid reproduction of [SZS 2022] (and also Anderson et al., 2016 thru now for online blitz).
Hazard Vs. Time—and Time Left

Switching to Komodo 13.3 in place of Stockfish 11 as analyzing engine:

- Average thinking time over all moves (turns 9–60): 181 seconds.
- IPR on turns of ≤ 0.5x hazard: 1635 +- 125.
- Average thinking time in those positions: 145 seconds.
- IPR on turns of ≥ 2x hazard: 2345 +- 125.
- Average thinking time in those positions: 151 seconds.

Results are more as-expected on turns with little time budget left:

- When player has ≤ 180 seconds left (633 turns): 1540 +- 280.
- Or average ≤ 60 seconds left to turn 40, not counting increment time: 1685 +- 200.
- Or average 30 seconds left to turn 40, counting half the increment time: 1395 +- 425. (In all cases, average hazard.)
Students in my CSE702 graduate seminar proposed a measure $H_U$ of entropy that uses only the move utilities $u_i$, not the projected probabilities $p_i$ (nor their logs). Avoids the rating feedback loop.

- Average $H_U = 2.57$.
- Turns with $H_U \leq 2$: avg. time used 88 sec., IPR 2405 +- 100.
- Turns with $H_U \leq 1.5$: avg. time used 72 sec., IPR 2485 +- 130.
- Turns with $H_U \leq 1$: avg. time used 56 sec., IPR 2645 +- 165 (lower hazard too).
- Turns with $H_U \leq 0.5$: avg. time used 40 sec., IPR 2580 +- 255 (much lower hazard).
- Turns with $H_U \geq 3$: time used 252 sec., IPR 2000 +- 35.
- Turns with $H_U \geq 3.5$ (702 pos.): time 312 sec., IPR 1965 +- 110.
- (No position has $H_U \geq 3.8$. All cases have close to mean hazard.)
- High entropy correlates well with (human experience of) difficulty.
- Much more work to do...
Discussion and Q & A

[And Thanks]

[Possible extra slides for Q & A follow...optional, of course...]
Cognitive Concepts and Conceits

Many results in cognitive decision making come from studies that

1. are well-targeted to the concept and hypothesis, but
2. have under 100 test subjects...
3. ...under simulated conditions...
4. ...with unclear metrics and alignment of personal vs. test goals..., and where
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.
Some Accompanying Stances

- Extreme Corner of Data Science—since I need ultra-high confidence on any claim.
- 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.
- **Cross-Validation**...one point of which is:
- How can we distinguish *uncovering genuine cognitive phenomena* from *artifacts of the model*?
### Time and Difficulty

#### Some Cognitive Nuggets

1. **Dimensions of Strategy and Tactics (and Depth of Thinking).**
   - But wait—the model has no information specific to chess...
   - Brain seems to register changes in move values as depth increases.

2. **Machine-Like Versus Human Play**
   - Garry Kasparov, as a 2012 Alan Turing Centennial test, distinguished 5 games played by human 2200-level masters from 5 games by engines “stopped down” to 2200 level.

3. **Relationship to Multiple-Choice Tests (with partial credits)**
   - “Solitaire Chess” feature often gives part credits.
   - Large field of **Item Response Theory (IRT)**.
Rating Inflation? Deflation?
- Note low Montreal 1979 IPRs.
- Even further deflation at the 1986 Men’s and Women’s Olympiads in Dubai.
- “Today’s players deserve their ratings.”
- Is human performance at chess improving as with physical sports? ...because of computers?

Growth Curves of Improving (Young) Players.
How To Manage Time Budget (basically, follow V. Anand!).
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 \(\approx\) 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.
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 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.
Now suppose the factual positivity rate is \textbf{1-in-50}.

We still have about \textbf{100} false positives, but now also \textbf{100} factual positives.

A positive from a 98\% test is here a 50-50 coinflip.

But a negative is \textit{good}:

- Only 2 false negatives will expect to come from the \textbf{100} dangerous people.
- From the \textbf{4,900} safe people, about \textbf{4,800} true negatives.
- Odds that your negative is false are \textbf{2,400-to-1} against.

\textbf{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.

\textbf{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. 1 false positive result.
2. 600 factual positives.
3. 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 $60/0.10 = 600$-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.
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)** from the raw metrics.
  - ROI is on same 0-100 scale as flipping a fair coin 100 times: 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**—no theoretical equation.
- Rapid and Blitz trained on **in-person** events in 2019. Slow chess trained on in-person FIDE Olympiads from 2010 to 2018.
- Does not account for the **difficulty** of games. That is the job of the full model.
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.

But this has perforce been post-normal science.

My “back of the envelope” formula held up over two years with only one small revision for preteens.

Larger revision in Oct. 2022 to curtail projections past Elo 2000 level.

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.

Show this GLL article including example of Ms. Velpula Sarayu.
The article’s larger subject is a **drastic** proposal by US statistician Jeff Sonas—long used by FIDE—to overhaul chess ratings below Elo 2000—that is, for beginning and amateur players. (This is on top of things I’ve been telling FIDE about ratings above 2000.)

My own work has been “tinged” by this issue.

A natural metric **apart** from both my model and Sonas’s domain cross-validates his observations and arguments.

I will now discuss some other applications that these solid foundations enable.
Hans Niemann: Platform or Plateau?

Ceci n'est pas un plateau

(celui-là, oui)
The Gender Gap in Chess

- 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?
- Picture emerging from recent youth events...?