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

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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)
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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 = $ gain/loss for right/wrong answer.
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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.
Time and Difficulty

Chess and Tests—With Partial Credits (Or LLMs?)

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A Difficult Trap (Kramnik-Anand, 2008 WC)
Aptitude—Via Elo Grades (calculator)

- Named for **Arpad Elo**, number $R_P$ rates skill of player $P$. 

Expectation $e = \frac{1}{1 + \exp(c(R - R_O))}$ depends only on difference to opponent's rating $R_O$. With $c = \frac{(\ln 10)}{400}$ the curve is:
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Position Value $\leftrightarrow$ Expectation (2000 vs. 2000)

Similar probability of 0.75 when up 1.30 vs. equal-rated player.

Complication: dependence on rating itself.

From 108883 turns in 1739 games:
#buckets in [0.01–10]: 365
Exp. up 0.50 = 0.6042
Exp. up 1.00 = 0.6987
Exp. up 2.00 = 0.8382
Exp. up 3.00 = 0.9136
60% exp. eval = 0.4794
70% exp. eval = 1.0072
80% exp. eval = 1.6695
90% exp. eval = 2.7578

Points frequency vs. eval for AA2000 SF7d00LREG2b100sk4

slope = 0.2117
skew = 0.0
drift = 0.0
$R^2 = 0.99999996$
B = 0.8921 + 0.01742
A = 0.02530 + 0.002571
K = 0.9747 + 0.002571
Q = 1.0
C = 1.0
nu = 1.0
Bootstrap B, x1000 trials:
B* = 0.9018 + 0.01829
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Item-Response Theory (IRT source)

The horizontal axis governs difficulty in relation to $\theta = \text{ability}$. The slope at $y = 0.5$ correctness rate is the discrimination factor.

Less difficult

More difficult

Probability

Ability

$\theta$
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![Graph showing Item-Response Theory](image)
Item-Response Theory (IRT source)

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Defining Difficulty

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

In chess, this is our $E_{L} = P_i (u_1 - u_i) = P_i \delta_i$.

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 $E_{L} \sim P_i p_i \log(1/p_1) - P_i p_i \log(1/p_i) = \log(1/p_1) - H$ where $H$ is entropy.

However, my model is double-log linear: $\log p_i \sim \exp(\delta_i)$.

Why double-log works and single-log fails.

How well does hazard—normalized over aptitude—work as a measure of difficulty?
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- Should we use metrics that say “A-level” etc. in each category? (Like *curving*).
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- **ASD**: Average difference in value from inferior moves (over all positions), but *scaled* down when one side has advantage.
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IPR and Hazard (World Senior Teams 2024)

Older players, established ratings (but deflated), average 2080. Focus on 2000–2200. Analysis by Stockfish 11 in EWN mode.

IPR overall: 2125 ± 40.

Broken down according to disadvantage:
- 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 ≥ 1.5 times normal hazard: 2255 ± 65.

With ≥ 2 x hazard: 2170 ± 115.

Could be consistent. But—

Positions of of 0.5 or lower hazard: 1800 ± 180.

Not constancy of signal. Low-hazard positions either have an obvious best move or many good moves.
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- 1–2 pawns behind: 2170 +- 105; worse: 2065 +- 110.
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- Within 1.00 of equal: 2145 +- 45; within 0.50: 2125 +- 65.

Reasonable constancy of signal.

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IPR and Hazard (World Senior Teams 2024)

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Low-hazard positions either have an obvious best move or many good moves.
Example: Niemann-Shankland, USA Ch. 2023

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.
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).
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5. Question is inherently complex or taxing.
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   Sunde, Zegners, and Strittmatter [SZS, Jan. 2022] propose counting the time (i.e., number of position nodes) needed by chess engine to complete analysis to depth (say) 24.
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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.

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Time-Quality Curves (whole graph)
Predicated on Time Spent For a Move

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

"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).
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- Positions on which they spent at most 30 seconds on the move:

\[
\begin{align*}
\text{2860} & \pm 75 \\
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\text{3220} & \pm 100 \\
\text{3230} & \pm 160 \\
\end{align*}
\]

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

- Positions with 5–10 minutes consumed:

\[
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- Using 10–15 minutes (705 positions):

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- Using \( \geq 15 \) minutes (371 positions):

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- Positions on which they spent at most 30 seconds on the move: $2860 \pm 75$.

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Hazard Vs. Time—and Time Left

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

- Overall IPR of Elo 2000-to-2200 players: 2175 ± 35.
- 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.)
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- Turns with $H_U \leq 1$: avg. time used 56 sec., IPR 2645 ± 165 (lower hazard too).
- 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.)
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Discussion and Q & A

[And Thanks]

[Possible extra slides for Q & A follow...optional, of course...]
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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.
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?
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   - Large field of Item Response Theory (IRT).
Time and Difficulty

Player Development

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?
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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 ≈ 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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Time and Difficulty

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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Time and Difficulty

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.
Covid in Non-Surge and Surge Times

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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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.

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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.

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Hans Niemann: Platform or Plateau?

Ceci n'est pas un plateau

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

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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?

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