Psychometric Modeling of Decision Making Via Game Play

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6. Derived Outputs:
   - Aggregate statistics: move-match MM, average error AE, \ldots
   - Projected confidence intervals for those statistics.
   - “Intrinsic Performance Ratings” (IPR’s).
**Data Sample**

Houdini 3, 32-pv mode, basic search depth 17 ply = 8-1/2 moves.

FEN: 2r3k1/1p1r3p/p5pR/P3pp2/3Pq3/2P1P3/1P1Q1RPP/6K1 b - - 0 32

dp/ex value diff move and PV

...  
17/53 +0.18 0.37 32...exd4 33.exd4 Re7...
17/53 +0.11 0.30 32...Rc4 33.g3 Ra4...
17/53 +0.08 0.27 32...Qb1+ 33.Rf1 Qa2...
17/53 +0.04 0.23 32...Qd5 33.Rh3 Re7...
17/53 +0.04 0.23 32...Re7 33.Rh3 Qd5...
17/53 0.00 0.19 32...Kg7 33.Rh3 Rc5...
17/53 -0.19 0.00 32...Rc5 33.b4 Rc4...

Best move at bottom, 19 centipawn advantage to Black, to move.  
These numbers and the move actually played (which was 32...Rc5) are the only chess-dependent inputs to the model.  
*Hence adaptable to any decision game with fungible values.*
Two Skill Parameters, Universal?

- **Sensitivity** $s$ divides eval-units to yield dimensionless quantities:
  
  \[ x_i = \frac{\Delta(v_1, v_i)}{s} \]

- **Consistency** $c$ magnifies high and low values of $x_i$.

Current model:

\[ \frac{\log(1/p_1)}{\log(1/p_i)} = \exp(-x_i^c). \]

- Higher $c$ makes the right-hand tinier, so $p_i$ tinier, thus reducing the frequency of blunders. “Tactical”
- Lower $s$ has a stronger effect on $x_i$ when $x_i$ is small, picking out slight differences. “Positional”
- **Depth** parameters are under development.
## Isomorphism With a Rasch Application

### Decision Making in Game Play

1. Values for move choices
2. Move-match (MM) score
3. Avg.-Error (AE) score
4. $P$-parameters
5. Model projections
6. Game criticality of position
7. “Intrinsic Perf. Rating” (IPR)

### Multiple-Choice Tests

1. Point credits for (all) answers
2. Best-answer score
3. Partial-credit score
4. Aptitude parameters ("position")
5. Difficulty of question
6. Weight of question
7. Grade assessment
8. Grade distribution analysis.

**Goal:** Cross-fertilize the rich data and theory between psychometrics and games.
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3. Intrinsic estimates of position difficulty?

4. Relate human performance to difficulty statistically.
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7. Game quality with unevenly-matched players.
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- Based on results of games (only): win, lose, draw.
- Numbers have only relative meaning.
- A 200-point difference $\sim 75\%$ expectation for the winner (now closer to 76%): “Class Unit” (László Mérő).
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- Advantages of IPR:
  - independent of opponent’s play
  - 50-100 games per year yield 1,500–3,000 relevant moves.
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Error Bars of measurement are based on the run over $T$. 
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- Game decisions modeled as independent, but really have “Sparse Dependence.” Adjustment reflects lower effective sample size $|T|$.
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Results and Interpretations

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Instead try to correlate observed difficulty with intrinsic features of the game position... such as how much values “swing” as analysis depth changes.
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5. Tame the curve of fallibility...
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The results so far show that this expectation is plausible.