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- Chess cheating detection needs both and more.
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4. “Person X made moves highly similar to Code Patch Y.”
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- Chess seems better for notions of depth.
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- Skill Assessment in One Number.

"I'm a 2370." Number has no absolute meaning—only rating differences matter. Difference of 200 has 75% expectation for higher player. Predictive content: your rating is the current best estimate of how you will perform in the next tournament. TPR: Tournament Performance Rating. Rating and TPR based only on results of games and ratings of opponents. Indeed relatively few games: 100 in a year is a lot for pro and amateur alike. Compare to 1,200 being a common need for a good election poll.
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- Also project standard deviation and confidence intervals.
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4. Defines fallible agent $P(s, c, \ldots)$.
5. Main Output: Probabilities $p_{t,i}$ for $P(s, c, \ldots)$ to select option $i$ at time $t$. 

Derived Outputs:
- Aggregate statistics: move-match $MM$, equal-top value $EV$, average scaled difference $ASD$, ...
- Projected confidence intervals: Bernoulli Trials + $j_T$-adjustment.
- IPRs similarly reflect errors from the regression.
Context: Decision-Making Model at Chess

1. Domain: A set \( T \) of decision-making situations \( t \).
   Chess game turns

2. Inputs: Values \( v_i \) for every option at turn \( t \).
   Computer values of moves \( m_i \)

3. Parameters: \( s, c, \ldots \) denoting skills and levels.
   Trained correspondence to chess Elo rating \( E \)

4. Defines fallible agent \( P(s, c, \ldots) \).

5. Main Output: Probabilities \( p_{t,i} \) for \( P(s, c, \ldots) \) to select option \( i \) at time \( t \).

6. Derived Outputs:
   - Aggregate statistics: move-match MM, equal-top value EV, average scaled difference ASD, \ldots
   - Projected confidence intervals: Bernoulli Trials + \( |T| \)-adjustment.
   - IPRs similarly reflect errors from the regression.
How the Model Operates

- Let $v_1, v_i$ be values of the best move $m_1$ and $i$th-best move $m_i$. 
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- Could be $h(p) = p \text{ (bad), log (good enough?), } H(p_i), \text{ logit.}$
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  \frac{h(p_i)}{h(p_1)} = 1 - x_i
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- Ratio not difference on LHS so $x_i$ on RHS has 0-to-1 scale.
- Given $(x_1, \ldots, x_i, \ldots, x_l)$, fit subject to $\sum_i p_i = 1$ to find $p_1$. Other $p_i$ follow by $p_i = h^{-1}(h(p_1)(1 - x_i))$. 
The Data (Before August 2015)

- Over 3 million moves of 50-PV data: > 250 GB.
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Is this “Big Data”? New sets being taken with UB CCR cluster.
For each Elo level $E$ training set, find $(s, c, \ldots)$ giving best fit.
Fitting and Fighting Parameters

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In frequentist view, can use many different fitting methods…
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  - Max-Likelihood does relatively poorly.

- Often $s$ and $c$ trade off markedly, but $E' \sim e(s, c)$ condenses into one Elo.
- Strong linear fit—suggests Elo mainly influenced by error.
The Turing Pandolfini?

- **Bruce Pandolfini** — played by Ben Kingsley in “Searching for Bobby Fischer.”
- Now does “*Solitaire Chess*” for Chess Life magazine:
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- Connect to parameters in **Item-Response Theory** (IRT) test-taking models. IRT does both skill and prediction.
Thus far using same formulas for both.
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Linchpin: Use best-available computer move values for assessment.
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  - Regress previous games by player.
  - Style is more “positional”? “tactical”?

Drawbacks: loss of neutrality and portability.

Can we find more properties in the raw numerical data?
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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)

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- How well do real humans perform on my ESP test??
Conditioned on one of the top two moves being played, if their values (Rybka 3, depth 13) differ by...:

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Last is not a typo—see post "When is a Law Natural?"

Similar 58%-42% split seen for any pair of tied moves. What can explain it?

Relation to slime molds and other "semi-Brownian" systems?
Conditioned on one of the top two moves being played, if their values (Rybka 3, depth 13) differ by...:

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- Formulate numerical measure of swing “up” and “down” (a trap).
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- Goal is to develop a *Challenge Quotient* based on how much trappy play a player sets for the opponent—and emself.
- Separates *performance* and *prediction* in the model.
Human Versus Computer Phenomena

Error Versus Advantage or Disadvantage

Humans, checked with four programs.

Computers

Position Eval

Houdini
Komodo
Rybka
StockFish
CEGT
The Imbalance-Error Phenomenon

- [show data]
- The metric correction

\[ \int_{e^{-\delta}}^{e} d\mu \quad \text{with} \quad d\mu = \frac{c}{c + x} \, dx \]

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(A) Human perception of value as proportional to stakes, per Ariely-Kahneman-Tversky.
(B) Rationally playing less catenaccio when marginal impact of evaluation on win probability is minimal. (Leo Stedile, working under Mark Braverman)
(C) Greater volatility intrinsic to chess as game progresses.
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(C) Greater volatility intrinsic to chess as game progresses.
A. Perception Proportional to Benefit

How strongly do you perceive a difference of 10 dollars, if:

- You are buying lunch and a drink in a pub.
- You are buying dinner in a restaurant.
- You are buying an I-pad.
- You are buying a car.

For the car, maybe you don’t care. In other cases, would you be equally thrifty?

*If you spend the way you play chess, you care maybe 4× as much in the pub!*
B. Rational Risk-Taking

- Expectation curves according to position evaluation $v$ are sigmoidal, indeed close to a hyperbolic tangent

$$E = \frac{e^{av} - e^{-av}}{e^{av} + e^{-av}}.$$
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- **How to test apart from cause A?**

- Expect eval-error curve to shift in games between unequally-rated players.

- Results so far show no shift—
Skill Assessment Versus Prediction in Game Play and Cheating Detection

Human Versus Computer Phenomena

![Graph showing win probability against evaluation of position with different curves for different comparisons: vs. all opponents, vs. 150+ higher, and vs. 150+ lower.](image)
Eval-Error Curve With Unequal Players

![Eval vs. AD for various strength opponents](image)
Some IPRs—Historical and Current

- Carlsen:
  - 2985 at London 2011 (Kramnik 2857, Aronian 2838).

- Kasparov:
  - Was playing 2860 to Karpov’s 2760 when 1984-85 match aborted.
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- **Kasparov:**
  - Was playing **2860** to Karpov’s **2760** when 1984-85 match aborted.
  - Both over **2800** in 1986, Kasparov **2905**.
  - Both under **2675** in New York-Lyon match 1990.
- **Bobby Fischer:**
  - **2920** over all 3 Candidates’ Matches in 1971.
  - **2650** vs. Spassky in 1972 (Spassky 2645).
  - **2725** vs. Spassky in 1992 (Spassky 2660).
- **Hou Yifan:** **2970** vs. Humpy Koneru (2685) in Nov. 2011.
- **Paul Morphy:** **2345** in 59 most imp. games, 2125 vs. Anderssen.
- **Capablanca:** **2935** at New York 1927.
- **Alekhine:** **2810** in 1927 WC match over Capa (2730).
### Computer and Freestyle IPRs


<table>
<thead>
<tr>
<th>Event</th>
<th>Rating</th>
<th>2σ range</th>
<th>#gm</th>
<th>#moves</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEGT g1,50</td>
<td>3009</td>
<td>2962–3056</td>
<td>42</td>
<td>4,212</td>
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<tr>
<td>CEGT g25,26</td>
<td>2963</td>
<td>2921–3006</td>
<td>42</td>
<td>5,277</td>
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<tr>
<td>PAL/CSS 5ch</td>
<td>3102</td>
<td>3051–3153</td>
<td>45</td>
<td>3,352</td>
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<tr>
<td>PAL/CSS 6ch</td>
<td>3086</td>
<td>3038–3134</td>
<td>45</td>
<td>3,065</td>
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<tr>
<td>PAL/CSS 8ch</td>
<td>3128</td>
<td>3083–3174</td>
<td>39</td>
<td>3,057</td>
</tr>
<tr>
<td>TCEC 2013</td>
<td>3083</td>
<td>3062–3105</td>
<td>90</td>
<td>11,024</td>
</tr>
</tbody>
</table>
Computer and Freestyle IPRs—To Move 60

Computer games can go very long in dead drawn positions. TCEC uses a cutoff but CEGT did not. Human-led games tend to climax (well) before Move 60. This comparison halves the difference to CEGT, otherwise similar:

<table>
<thead>
<tr>
<th>Sample set</th>
<th>Rating</th>
<th>2σ range</th>
<th>#gm</th>
<th>#moves</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEGT all</td>
<td>2985</td>
<td>2954–3016</td>
<td>84</td>
<td>9,489</td>
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<tr>
<td>PAL/CSS all</td>
<td>3106</td>
<td>3078–3133</td>
<td>129</td>
<td>9,474</td>
</tr>
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<td>3083</td>
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<tr>
<td>CEGT to60</td>
<td>3056</td>
<td>3023–3088</td>
<td>84</td>
<td>7,010</td>
</tr>
<tr>
<td>PAL/CSS to60</td>
<td>3112</td>
<td>3084–3141</td>
<td>129</td>
<td>8,744</td>
</tr>
<tr>
<td>TCEC to60</td>
<td>3096</td>
<td>3072–3120</td>
<td>90</td>
<td>8,184</td>
</tr>
</tbody>
</table>
Degrees of Forcing Play

Forcing Index (2500 perspective)

- Computer (avg.): 49
- Human: 53.3
Add Human-Computer Tandems

Evidently the humans called the shots. But how did they play?

Forcing Index (2500 perspective)

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Evidently the humans called the shots.
Evidently the humans called the shots. But how did they play?
Adding 210 Elo was significant. Forcing but good teamwork.
2014 Freestyle Tournament Performance

Forcing Index (2500 perspective)

- Computer (avg.): 49
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2895 in 2007-08
3085 in late 2013
3105 in 2007-08
3020 ? early 2014

Tandems had marginally better W-L, but quality not clear...
Add Topalov Forcing Kramnik

Forcing Index (2500 perspective)

- Computer (avg.): 49
- Computer+Human: 54.5
- Human: 53.3
- Kramnik (2006 g2): 74.5

Last bar goes way off the chart
Is There Room to Grow?

- In *chess*, alas some hints of “no.”
- If (randomizing) **3200**-level programs can score 10% against any strategy, then no strategy can ever exceed **3550**.
- In 2010–2014 many more games between players rated under 1600 and between **2800**+ became available.
- Analysis in my model shows a **linear** relationship between rating and my Average Scaled Difference ASD statistic clear down to **1200** level.
- The **y-intercept** of the line is consistently near **3370**.
- But Komodo and Stockfish on 4-core PCs are rated **over 3370** on CCRL. How can this be?
  - Well, CCRL uses a 40 moves in 40 minutes time control. Other lists use other times and show ratings still in the 3100s.
- Best explanation: IPR correlates 85–90% with ASD and 10–15% with move-matching—which has y-intercept near **4500**.
Solution and Opportunities

- Hence my model projects a ceiling around \textbf{3500-3550}.
- Still not much room to grow... in chess that is.
- This may already explain the diminishing returns from adding humans... in chess.
- But the larger marriage of \textbf{Shallow but Broad} to \textbf{Deep but Narrow} that was theoretically driving the gains still has potential.
- Revisit trying to “humanize” chess programs?
- Complexity theory classifies chess as “Hard to Parallelize.”
- Whether \textbf{chess endgame tables} are “\textbf{Associatively Compressible}” is an indicator worth pursuing.
- Model has many other applications: study human performance under distraction; design multiple choice tests to standards of difficulty; extend \textit{intrinsic} Elo quality measures to other domains.
Conclusions

- Lots more potential for research and connections...
- Can use support—infrastructure, student helpers...
  - Run data with other engines Houdini, Stockfish, Komodo....
  - Run more tournaments.
  - Run to higher depths—how much does that matter?
- Spread word about general-scientific aspects, including public outreach over what isn’t (and is) cheating.
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- Learn more about human decision making.
- Thus the Turing Tour comes back to the human mind.
- Thank you very much for the invitation.