Chess and Informatics

Kenneth W. Regan
University at Buffalo (SUNY)

CISIM 2017 Keynote

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- Now: chess gives a window on CS advances and data-science problems.

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- Real story IMHO is **benchmarking**: *How much measurable problem-solving power can we get out of a machine?*

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- Embraced by the politics and sports prediction website *FiveThirtyEight*.

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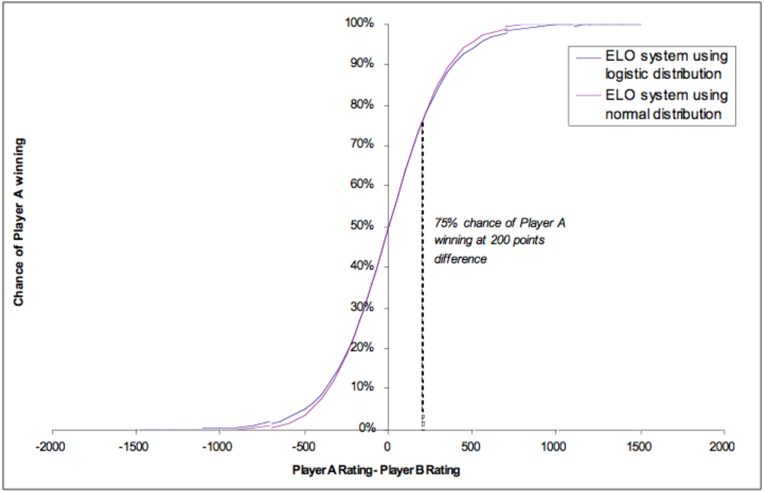
- *FiveThirtyEight* centers on 1500 and rated Golden State at 1850, Cavaliers at 1691 before the NBA Finals began: 28.6% chance for Cavs per game, about 11% for 7-game series.

Expectation Curve for Elo Differences



Source: http://www.mrscienceshow.com/2009/06/sumo-vs-chess-how-their-ranking-systems.html

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- **3400-3500**: Ceiling of perfect play??

László Mérő, *Ways of Thinking* (1990): Chess has *human depth* of 11 (or 14) *class units* of 200 Elo, 14 (or 17) including computers.

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- *Basic branching factor* $\ell \approx 35$ legal moves on average.

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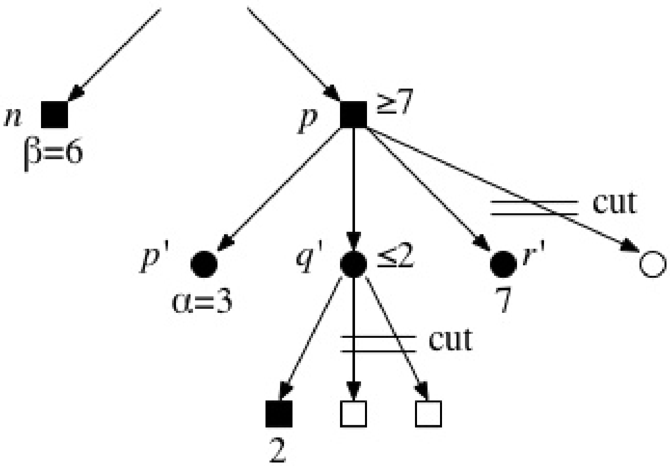
- Successful α-β *pruning* reduces branching factor to $\approx \sqrt{\ell}$.

Alpha-Beta Search—Diagram



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- Nominal depth d really a mix of depth c and depth D; actual visited nodes are mostly wrapped around the PV. **How effective?**

The Logistic Law...

What percentage e of points do human players (of a given rating R) score from positions that a program gives value v?

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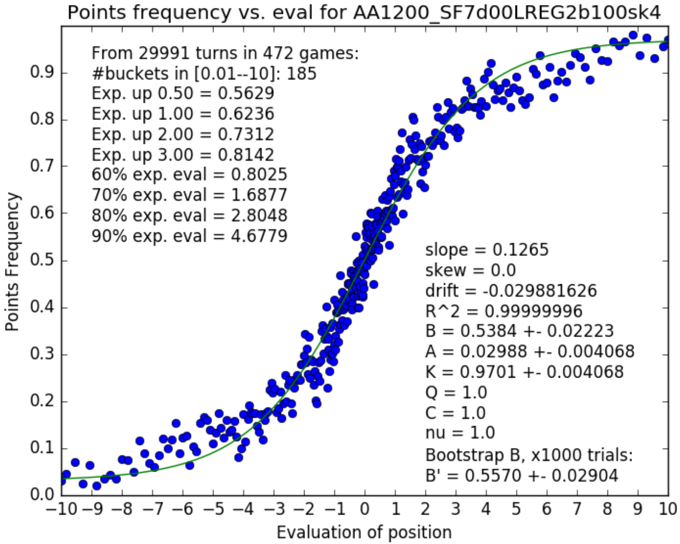
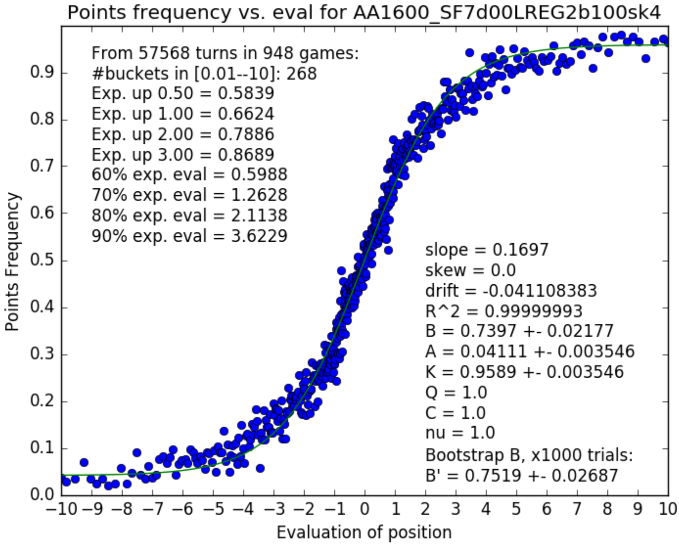
Data from all available games at standard time controls with both players rated within 10 (or 12) of an Elo quarter-century point **1025**, **1050**, **1075**, **1100**, . . . , **2800**. From 1,000s to 100,000s of positions in each group, just over 3 million positions total.

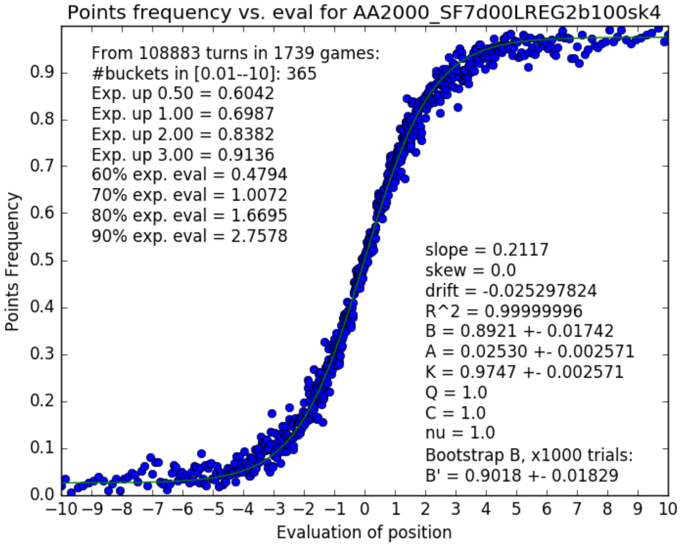
Example: Elo 1200



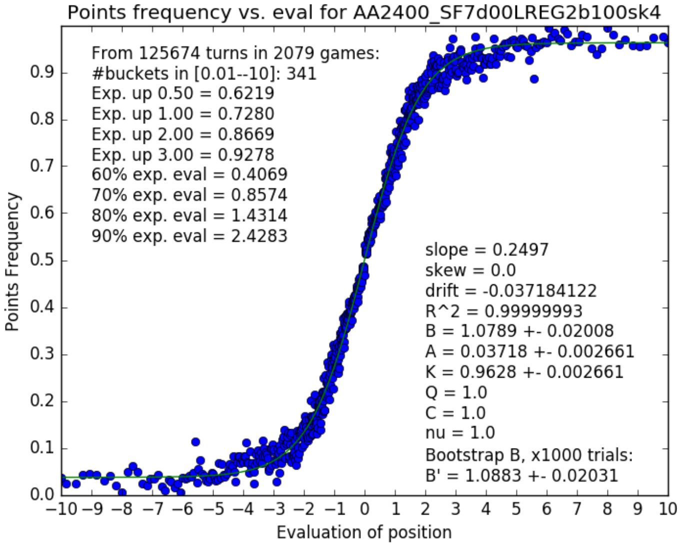
Example: Elo 1600



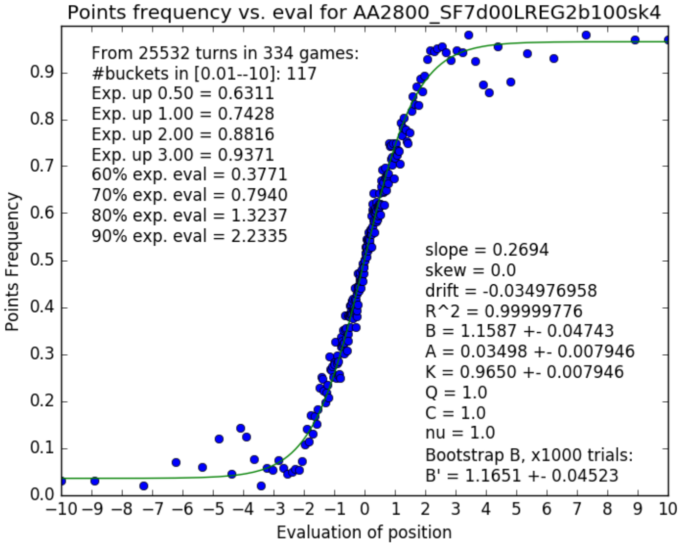
Example: Elo 2000



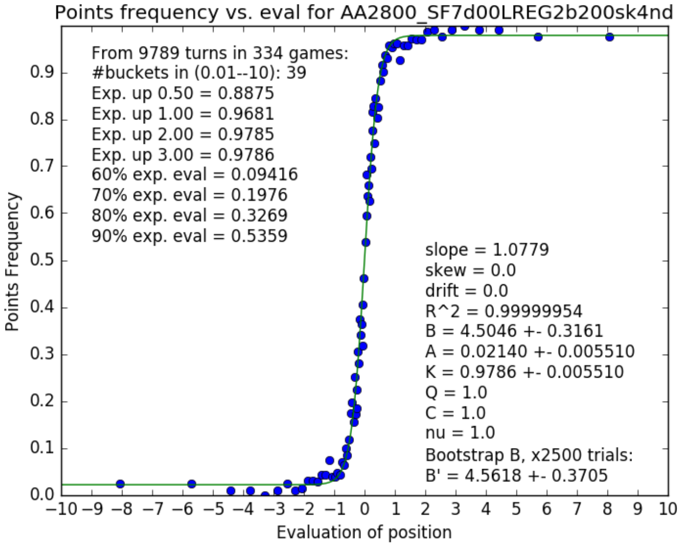
Example: Elo 2400



Example: Elo 2800



Example: Elo 2800 Ignoring Draws



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   - That is, if one program values a Queen as 9 and another says 10, you might expect to convert the latter by 9/10.
4. Higher B for higher rating thus means we *perceive values more sharply*.

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- Some commercial programs do such transformations after-the-fact.
- The open-source Stockfish program does not.
- Amir Ban, co-creator of both the chess program Deep Junior and the USB flash drive, attests that the law comes from doing things naturally and maximizes predictivity as well as playing strength for programs.

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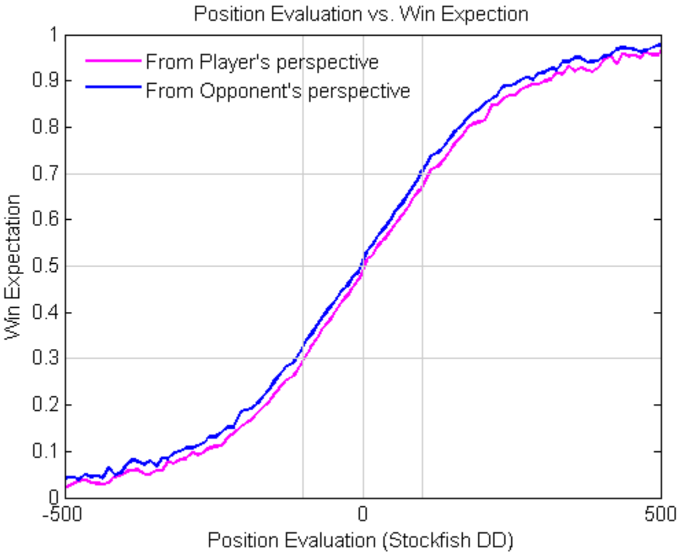
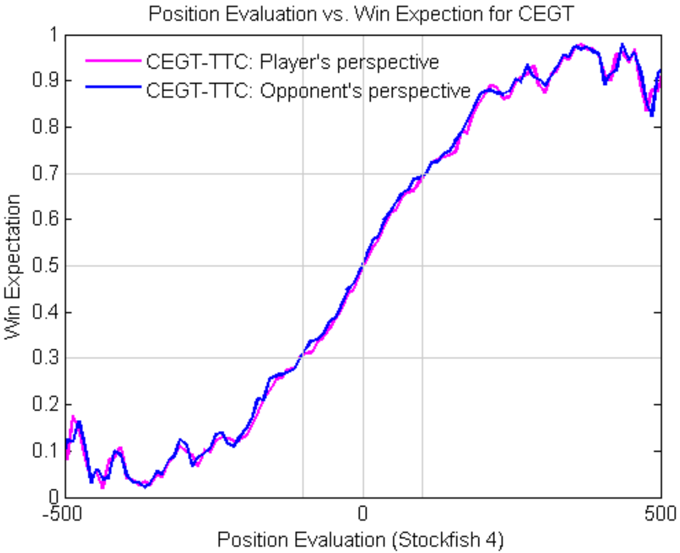
- GM Savielly Tartakover (Polish: Ksawey Tartakower, born in Rostov-on-Don): "The game is won by the player who makes the next-to-last blunder."

Tartakover's Dictum. . .



. . . Is Not True for Computers



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- **2006**: WC Vladimir Kramnik loses to Deep Fritz 10 on ordinary quad-core PC by 4-2; he overlooks Mate-in-1 in one game.

No human GM has played a computer on even terms in a sponsored match since then.

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- Predicted cost: $\sum_{i=1}^{\ell} p_i \delta_i$. *Scaled* down when $|v_1|$ is high.

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6. Derived Outputs (*Aggregate Statistics*):

$$\begin{aligned}
\textbf{MM} &= \sum_t p_{1,t} && \textit{Move-Match} \\
\textbf{EV} &= \sum_t \sum_{i:\delta_{i,t}=0} p_{i,t} && \textit{Equal-top Value} \\
\textbf{ASD} &= \sum_t \sum_i p_{i,t}\delta_{i,t} && \textit{Average Scaled Difference.}
\end{aligned}$$

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- Then calculate p_1 to make $\sum_i p_i^{u_i} = 1$.

Given $u_1, \ldots, u_\ell \geq 1$, how to solve for p giving $p^{u_1} + \cdots + p^{u_\ell} = 1$? Better way than Newton?

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- Not only yields linear relation $E = \alpha s + \beta c$ to Elo rating, but the training gives good progressions $[s_E]$ and $[c_E]$ in each parameter.
- Unique fit and *Intrinsic Performance Rating* (IPR) for any set of games.

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Co? Note: Sample sizes are 2,605–7,701 positions each, out of 140,999 positions by 2000-rated players overall.

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- Stockfish 7 would not diminish in game-playing quality at all if m_1 and m_2 were switched in those situations. How can we "precognite" which one it will list first??? An ESP test that humans pass over **60%**.

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- Separates *performance* and *prediction* in the model.

Example of "Swing" over Increasing Depths

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

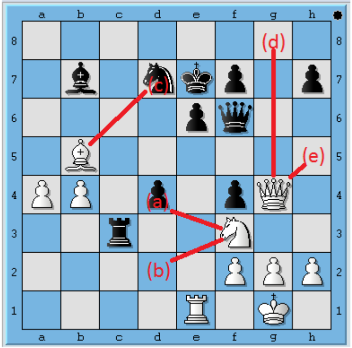
(c) proliferation . . blighted

(d) destruction . . disputed

(e) disappearance . . frustrated

(source: itunes.apple.com)

=



Move	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Nd2	103	093	087	093	027	028	000	000	056	-007	039	028	037	020	014	017	000	006	000
Bxd7	048	034	-033	-033	-013	-042	-039	-050	-025	-010	001	000	-009	-027	-018	000	000	000	000
Qg8	114	114	-037	-037	-014	-014	-022	-068	-008	-056	-042	-004	-032	000	-014	-025	-045	-045	-050
...			...			...			...			...			...			...	
Nxd4	-056	-056	-113	-071	-071	-145	-020	-006	077	052	066	040	050	051	-181	-181	-181	-213	-213

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- But those fits usually give $h > 1.5$, **Uh-Oh!**

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- Separates prediction and performance-assessment components.
- Often accurately predicts inferior moves to be more likely, **But...**

Fine-Grained Trouble Under the Dial

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- [show examples from web article, "Stopped Watches and Data Analytics"]

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- Even sometimes gives ϵ projection to the best move!
- [show examples from web article, "Stopped Watches and Data Analytics"]
- So far the cause seems to be that the fit is latching on to features of ρ_i that allow it to be welded onto the frequency histogram $f_1, f_2, f_3, \ldots$.

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- And by the University of Washington—Seatle course `http://callingbullshit.org/`.

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1. Increase research on AI systems for Big Data and Deep Learning with emphasis on moral constraints.
2. Increase research on AI systems for Big Data and Deep Learning with emphasis on the prevention of AI systems to be hacked.
3. Establish (a) a committee of Data Authorities and (b) an ethical committee.

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- Thank you very much for the invitation!