Chess and Informatics

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CISIM 2017 Keynote
Chess and CS...

Chess: “The Drosophila of AI” (Herbert Simon, John McCarthy, after Alexander Kronod)

Advice for AI grad students 10 years ago: “Don’t do chess.” (I’ve lost my source but see Daniel Dennett, “Higher-order Truths About Chess” [sic], 2006)

From 1986 to 2006, I followed this advice. Turned down many requests for what I saw as “me too” computer chess. Main area = computational complexity, in which I also partner Richard Lipton’s popular blog.

Then came the cheating accusations at the 2006 world championship match...

Now: chess gives a window on CS advances and data-science problems.
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External History of Computer Chess: Part One

1950s: Papers by Turing, Shannon, Newell-Simon-Shaw, others...,
programs by Prinz, Bernstein, Russian BESM group.

1960s: First programs able to defeat club-level players.

1968: David Levy, International Master (my rank) bet McCarthy and Newell $1,000 that no computer would defeat him by 1978.

1978: Levy defeats Chess 4.7 by 4.5–1.5 to win bet, but computer wins first ever game over master.

1981: Cray Blitz (software by Robert Hyatt) achieves first "Master" rating, followed soon by Ken Thompson's Belle.

1988: HiTech by Hans Berliner of CMU defeats grandmaster (GM) Arnold Denker in match; Deep Thought by another CMU group defeats GM and former world championship candidate Bent Larsen in a tournament game.

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Chess was a microcosm of human thinking.

"Chess Knowledge" approach persisted into the 1970s.

"Brute Force" was considered dominant by the 1980s.

Hsu et al. (1990) noted the "emulation" and "engineering" camps.

"It may seem strange that our machine can incorporate relatively little knowledge of chess and yet outplay excellent human players. Yet one must remember that the computer does not mimic human thought—it reaches the same ends by different means."

Forecast that a basic search depth of 14–15 plies from raw speed of 1 billion positions per second would give an Elo Rating of 3400.

Real story, in my humble opinion, is benchmarking: How much measurable problem-solving power can we get out of a machine?
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Benchmarks and Ratings

Famous benchmarks:
Whetstones, Dhrystones, mega/giga/tera/peta-FLOPS via LINPACK, IOzone, ...

Other benchmarks across business suites, embedded computing functions...

Whole-system benchmarking is harder.

Do we include human software acumen?

Ratings ground performance in human competitive arenas.

Personnel evaluation tests and other psychometrics are partial like course grades...

Elo Ratings originated for chess by Arpad Elo in the US in the 1950s.
Adopted by the World Chess Federation (FIDE) from 1971 on.
Used by some other sporting bodies.
Embraced by the politics and sports prediction website FiveThirtyEight.
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- Makes a 200-point difference \textup{==} just over 75% expectation.
- Adding $e$ over every game in a tournament yield expected score $e_P$.
- New rating is $R'_P = R_P + K \cdot (s_P - e_P)$ where $s_P$ is $P'$s actual score and the factor $K$ is set by policy (e.g. $K = 10$ for established players but $K = 40$ for young/novice/rapidly improving ones).
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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

Chess Ratings and “Human Depth”

600: Adult beginner (scholastics go under 100...)
1000: Minimum FIDE rating, beginning tournament player.
1500: Solid club player.
2200: Master.
2500: Typical Grandmaster.
2800: Human championship level.
3200: Exceeded by today’s best programs on commodity PCs.
3400-3500: Ceiling of perfect play??
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Game Representation + Evaluation + Search

Game Representation

- Hardware advances and software tricks.

Evaluation

- Base evaluation $e(p)$ for each position $p$.
- Typically linear: $P_j w_j (\text{value of factor } j)$.
- Factors begin with 1 for each pawn, 3+ for Knight, 3++ for Bishop, 5 per Rook, 9 (or 10 or...) for the Queen, then go into many "positional" elements.
- Weights $w_i$ now automatedly "tuned" by extensive game testing.
- Eval in discrete units of 0.01 called centipawns.

Search

- Minimax search: $e(d(p)) = \max_i e(d(p[m_i]))$.
- Negate eval for opponent's view and recurse: negamax search.

Basic branching factor

- $35$ legal moves on average.
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Programs for Chess and Other Games

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- Eval in discrete units of 0.01 called centipawns.
- Minimax search: $e_d(p) = \max_{i \leq \ell(p)} e_{d-1}(p[m_i])$.
- Negate eval for opponent’s view and recurse: negamax search.
Programs for Chess and Other Games

Game Representation + Evaluation + Search

- Game Rep.: Hardware advances and software tricks.
- Base evaluation $e_0(p)$ for each position $p$.
- Typically linear: $\sum_j w_j$ (value of factor $j$).
- Factors begin with 1 for each pawn, 3+ for Knight, 3++ for Bishop, 5 per Rook, 9 (or 10 or...) for the Queen, then go into many “positional” elements.
- Weights $w_i$ now automatedly “tuned” by extensive game testing.
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- Minimax search: $e_d(p) = \max_{i \leq \ell(p)} e_{d-1}(p[m_i])$.
- Negate eval for opponent’s view and recurse: negamax search.
- Basic branching factor $\ell \approx 35$ legal moves on average.
If we already know an opponent reply $n_2$ to move $m_2$ that makes $e_{d1}(p[m_2]) < e_{d1}(p[m_1])$, then no need to search any other replies to $m_2$. We need not be precise about values far from $v = e_{d1}(p)$. Hence we can save by guessing not just $v$ but a window $<v<$ around $v$, using "<" and ">" as boundary "cutoff" values. If we guess wrong and it appears $v<$ ("fail low") or $v>$ ("fail high"), widen the window and start over. Successful-pruning reduces branching factor to $p`.
Sound Search Principles

- If we already know an opponent reply $n_2$ to move $m_2$ that makes $e_{d-1}(p[m_2]) < e_{d-1}(p[m_1])$, then no need to search any other replies to $m_2$. 
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- We need not be precise about values far from $v = e_d(p)$.
- Hence we can save by guessing not just $v$ but a window $\alpha < v < \beta$ around $v$, using “$\alpha$” and “$\beta$” as boundary “cutoff” values.
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- Hence we can save by guessing not just $v$ but a window $\alpha < v < \beta$ around $v$, using “$\alpha$” and “$\beta$” as boundary “cutoff” values.
- If we guess wrong and it appears $v < \alpha$ (“fail low”) or $v > \beta$ (“fail high”), widen the window and start over.
- Successful $\alpha$-$\beta$ pruning reduces branching factor to $\approx \sqrt{l}$.
Alpha-Beta Search—Diagram
Iterative Deepening

Work in rounds of search $d = 1; 2; 3; \ldots$; use rankings of moves at $d_1$ to optimize pruning: "try the best moves first."

Use value $v_{d_1}$ as best guess for $v_{d}$ to center the window.

Extend search to depths $D > d$ along lines of play that have checks and captures and/or moves that are singular (meaning next-best move is much worse).

Stop extending when line becomes quiescent.

Each stage yields a well-defined principal variation ($PV$) along which:

$$e_d(p) = e_{d_1}(p_0) = e_0(p(D))$$

Stop when time budget dictates making a move.

Values $v_1; v_2; v_3; \ldots; v_{d}; \ldots$ converge to "true value."
Iterative Deepening

- Work in *rounds of search* $d = 1, 2, 3, \ldots$
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- Work in *rounds of search* $d = 1, 2, 3, \ldots$
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- Values $v_1, v_2, v_3, \ldots, v_d, \ldots$ converge to “true value.”
“Soundy” Search Principles

Often one can “prove” cutoffs faster by letting the other player make two moves in a row. Unsound for Zugzwang positions (where you want your opponent not you to have to move), but there are smart ways to avoid being fooled by them. Evaluate inferior moves only to depth $c_d$. These “Null Move” and “Late Move” reduction heuristics do the most to reduce the operational branching factor to about 1.5–1.6(!)

Note: $1^{55}_4^{40}_6^{10}=10^{60}$ million(!)

The champion program Stockfish 8 reaches depth 40 within an hour on my laptop.

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

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

Answer:

$$e \approx \frac{1}{1 + e^{-Bv}},$$

where $B$ depends on $R$. 
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Exact fit to $A + \frac{1 - 2A}{1 + \exp(-Bv)}$ where $A$ is small; $A$ represents the chance of missing a checkmate or otherwise blowing a “completely winning” game.
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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

From 29991 turns in 472 games:
#buckets in [0.01--10]: 185
Exp. up 0.50 = 0.5629
Exp. up 1.00 = 0.6236
Exp. up 2.00 = 0.7312
Exp. up 3.00 = 0.8142
60% exp. eval = 0.8025
70% exp. eval = 1.6877
80% exp. eval = 2.8048
90% exp. eval = 4.6779

slope = 0.1265
skew = 0.0
drift = -0.029881626
R^2 = 0.99999996
B = 0.5384 ± 0.02223
A = 0.02988 ± 0.004068
K = 0.9701 ± 0.004068
Q = 1.0
C = 1.0
nu = 1.0
Bootstrap B, x1000 trials:
B' = 0.5570 ± 0.02904
Example: Elo 1600

From 57568 turns in 948 games:
#buckets in [0.01--10]: 268
Exp. up 0.50 = 0.5839
Exp. up 1.00 = 0.6624
Exp. up 2.00 = 0.7886
Exp. up 3.00 = 0.8689
60% exp. eval = 0.5988
70% exp. eval = 1.2628
80% exp. eval = 2.1138
90% exp. eval = 3.6229

slope = 0.1697
skew = 0.0
drift = -0.041108383
R^2 = 0.99999993
B = 0.7397 +/- 0.02177
A = 0.04111 +/- 0.003546
K = 0.9589 +/- 0.003546
Q = 1.0
C = 1.0
nu = 1.0
Bootstrap B, x1000 trials:
B' = 0.7519 +/- 0.02687
Example: Elo 2000

Points frequency vs. eval for AA2000_SF7d00LREG2b100sk4

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

slope = 0.2117
skew = 0.0
drift = -0.025297824
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
Chess and Informatics

Example: Elo 2400

Points frequency vs. eval for AA2400_SF7d00LREG2b100sk4

From 125674 turns in 2079 games:
- #buckets in [0.01--10]: 341
- Exp. up 0.50 = 0.6219
- Exp. up 1.00 = 0.7280
- Exp. up 2.00 = 0.8669
- Exp. up 3.00 = 0.9278
- 60% exp. eval = 0.4069
- 70% exp. eval = 0.8574
- 80% exp. eval = 1.4314
- 90% exp. eval = 2.4283

slope = 0.2497
skew = 0.0
drift = -0.037184122
R^2 = 0.99999993
B = 1.0789 +- 0.02008
A = 0.03718 +- 0.002661
K = 0.9628 +- 0.002661
Q = 1.0
C = 1.0
nu = 1.0

Bootstrap B, x1000 trials:
B' = 1.0883 +- 0.02031
Example: Elo 2800

From 25532 turns in 334 games:

- #buckets in [0.01--10]: 117
- Exp. up 0.50 = 0.6311
- Exp. up 1.00 = 0.7428
- Exp. up 2.00 = 0.8816
- Exp. up 3.00 = 0.9371
- 60% exp. eval = 0.3771
- 70% exp. eval = 0.7940
- 80% exp. eval = 1.3237
- 90% exp. eval = 2.2335

slope = 0.2694
skew = 0.0
drift = -0.034976958
R^2 = 0.99999776
B = 1.1587 +- 0.04743
A = 0.03498 +- 0.007946
K = 0.9650 +- 0.007946
Q = 1.0
C = 1.0
nu = 1.0
Bootstrap B, x1000 trials:
B' = 1.1651 +- 0.04523
Example: Elo 2800 Ignoring Draws

From 9789 turns in 334 games:
#buckets in (0.01--10): 39
Exp. up 0.50 = 0.8875
Exp. up 1.00 = 0.9681
Exp. up 2.00 = 0.9785
Exp. up 3.00 = 0.9786
60% exp. eval = 0.09416
70% exp. eval = 0.1976
80% exp. eval = 0.3269
90% exp. eval = 0.5359

slope = 1.0779
skew = 0.0
drift = 0.0
R^2 = 0.99999954
B = 4.5046 +- 0.3161
A = 0.02140 +- 0.005510
K = 0.9786 +- 0.005510
Q = 1.0
C = 1.0
nu = 1.0
Bootstrap B, x2500 trials:
B' = 4.5618 +- 0.3705
Significances
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4. Higher $B$ for higher rating thus means we perceive values more sharply.
The Logistic Law ... is Technically False

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- 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.
A Second Tweak to the Logistic Law

Conditioned on the position having value $v$ from your point of view, would you rather have it be your turn to move or the opponent’s?
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- Measured difference of 3–4% in expectation.
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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

1998: Kasparov says, “if you can’t beat ‘em, join ‘em” and promotes Advanced Chess where players team with one computer. (Freestyle Chess allows any number of computers; major events sponsored in 2005–2008 and 2014.)

1999–2003: Smaller systems beat GMs but only tie with Kasparov and later World Champion Viswanathan Anand.


2005: Souped-up Hydra crushes GM Michael Adams 5.5-0.5.

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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History of Computer Chess – Part Deux

2006: GM Veselin Topalov accuses Kramnik of getting moves from Fritz 9 by Internet cable to his toilet—the only off-camera part of their 2006 WC match milieu. Only evidence given was alleged too-high “coincidence rates” of Kramnik’s moves with those liked by Fritz 9. Frederic Friedel, co-founder of Fritz maker ChessBase: “Can anyone help us evaluate such statistical accusations?”

2009: Smartphone “Pocket Fritz” measured at 2900+ performance crushing 2250-level human players 9.5–0.5.

2010: First later-proven case involving top-100 player.

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Chess is a hard problem. Narrowly defined but needs broad resources. Advances in hardware first. Later trumped by advances in software. Albert Silver 2014 experiment: Komodo 8 on smartphone trounced 2006 leader Shredder 9 on hardware 50 times faster. Still not emulating the human mind... But powerful enough to "scope" players' minds... aided by acuity in modeling.
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Predictive Models

Given data and analysis on potential events $E_1, \ldots, E_L$ estimate probabilities $p_1, \ldots, p_L$ for them to occur.

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- The events are the legal moves in a chess position. They are *mutually exclusive* and (together with “draw” or “resign”) *collectively exhaustive*: $\sum_i p_i = 1$. 

Cost of a (non-optimal) move $m_i = \|v_1 - v_i\|$ to the first move $m_1$. 

Predicted cost: $P_{\text{predicted}} = \sum_i p_i \cdot i$. 

Scaled down when $|v_1|$ is high.
Given data and analysis on potential events $E_1, \ldots, E_L$ estimate probabilities $p_1, \ldots, p_L$ for them to occur.

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- Some of the events $E_1, \ldots, E_m$ are natural disasters.
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- The events are the legal moves in a chess position. They are mutually exclusive and (together with “draw” or “resign”) collectively exhaustive: $\sum_i p_i = 1$.
- Cost of a (non-optimal) move $m_i = \delta(v_1, v_i)$ to the first move $m_1$. 

Predictive Models
Given data and analysis on potential events $E_1, \ldots, E_L$ estimate probabilities $p_1, \ldots, p_L$ for them to occur.

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- The events are the legal moves in a chess position. They are *mutually exclusive* and (together with "draw" or "resign") *collectively exhaustive*: $\sum_i p_i = 1$.
- Cost of a (non-optimal) move $m_i$ is $\delta_i = \delta(v_1, v_i)$ to the first move $m_1$.
- Predicted cost: $\sum_{i=1}^{L} p_i \delta_i$. *Scaled down* when $|v_1|$ is high.
Inputs and Outputs

Domain: A set $T$ of decision-making situations $t$.

Chess game turns

Inputs: Values $v_i$ for every option at turn $t$.

Parameters: $s; c; \ldots$ denoting skills and levels.

Defines fallible agent $P(s; c; \ldots)$.

Main Output: Probabilities $p_i; t$ for $P(s; c; \ldots)$ to select option $i$ at time $t$.

Derived Outputs (Aggregate Statistics):

- Move-Match $MM = \sum_t p_i; t$
- Equal-top Value $EV = \sum_t \sum_i: i; t = 0 p_i; t$
- Average Scaled Difference $ASD = \sum_t \sum_i p_i; t - i; t$

And confidence intervals for them via multinomial Bernoulli trials.
Domain: A set $T$ of decision-making situations $t$. Chess game turns
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Derived Outputs (Aggregate Statistics):
- $MM = \sum t p_{1,t}$:
- $EV = \sum t \sum i p_{i,t}$:
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Derived Outputs (Aggregate Statistics):

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\text{MM} = \sum_{t} p_{1,t} \quad \text{Move-Match}
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\[
\text{ASD} = \sum_{t} \sum_{i} p_{i,t} \delta_{i,t} \quad \text{Average Scaled Difference}
\]
Obtaining the Probabilities

Each move \( m_i \) is assigned a perceived inferiority \( z_i \). Dimensionless, not in centipawn units like \( i \).

Exponential decay:

\[
p_i = p_g(z_i)
\]

where \( g(0) = 1 \), \( u_i = g(z_i) \) is the “utility share curve.”

Could be \( g(z_i) = z_i + 1 \) but a second layer of exponentiation works better (so far).

Have used \( g(z) = e^z \) and \( g(z) = e^z + 1 \); the latter makes \( 1 = g(z) \) a “folded” logistic curve.

Then calculate \( p_1 \) to make \( P_i p_u_i = 1 \).

Given \( u_1 ; \ldots ; u_n \), how to solve for \( p \) giving \( p u_1 + p u_n = 1 \)? Better way than Newton?
Obtaining the Probabilities

- Each move $m_i$ is assigned a perceived inferiority $z_i \geq 0$. 

Exponential decay:

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Given $u_1, \ldots, u_l$, how to solve for $p$ giving $p_u + \cdots + p_u = 1$? Better way than Newton?
Obtaining the Probabilities

- Each move $m_i$ is assigned a perceived inferiority $z_i \geq 0$.
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$Exponential$ decay:\ $p_i = p_g(z_i)^1$; where $g(0) = 1$, $u_i = g(z_i)^1$ is the "utility share curve." Could be $g(z_i) = z_i + 1$ but a second layer of exponentiation works better (so far).

$Have used$ $g(z_i) = e^{z_i}$ and $g(z_i) = e^{z_i} + 1^2$; the latter makes $1 = g(z_i)$ a "folded" logistic curve.

Then calculate $p_1$ to make $P_i p_u i = 1$. Given $u_1$; $\ldots$ $u_n$, how to solve for $p$ giving $p u_1 + \ldots + p u_n = 1$? Better way than Newton?
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- Each move $m_i$ is assigned a perceived inferiority $z_i \geq 0$.
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- Have used $g(z) = e^z$ and $g(z) = \frac{e^z + 1}{2}$; the latter makes $1/g(z)$ a “folded” logistic curve.
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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?
Inferiority Main Equation

\[ z_i = \left( \frac{\delta_i}{s} \right)^c \]
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- Parameters \( s \) for sensitivity, \( c \) for consistency.
Inferiority Main Equation

\[ z_i = \left( \frac{\delta_i}{s} \right)^c \]

- Parameters \( s \) for *sensitivity*, \( c \) for *consistency*.
- \( \partial s \) greatest near \( \delta_i = 0 \); \( \partial c \) takes over for large mistakes.
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- Parameters \( s \) for sensitivity, \( c \) for consistency.
- \( \partial s \) greatest near \( \delta_i = 0 \); \( \partial c \) takes over for large mistakes.
- Given any sample of positions, fit \( s, c \) to make projected MM and ASD agree with the sample values.
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- Given any sample of positions, fit \( s, c \) to make projected MM and ASD agree with the sample values.
- Makes MM and ASD into unbiased estimators (EV generally conservative).
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- **Monotone** in sense that better moves always get higher probability no matter how weak the player, and an uptick in the value of a move always increases its probability.
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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.
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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.
How Sensitive Are We?

Conditioned on the best move $m_1$ being superior to $m_2$ by $x$ and one of $m_1$ or $m_2$ being played, with what frequency $f_1$ do 2000-rated players prefer $m_1$?

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

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- \( x = 0.01 \),

- \( x = 0.02 \),

- \( x = 0.03 \),

- \( x = 0.04 \),

- \( x = 0.05 \),

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- $x = 0.01, f_1 = 52.85\%$. 

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- $x = 0.01$, $f_1 = 52.85\%$.
- $x = 0.02$, $f_1 = 53.83\%$.
- $x = 0.03$, $f_1 = 56.08\%$.

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- $x = 0.03$, $f_1 = 56.08\%$.
- $x = 0.04$, $f_1 = 56.165\%$.

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How Sensitive Are We?

Conditioned on the best move $m_1$ being superior to $m_2$ by $x$ and one of $m_1$ or $m_2$ being played, with what frequency $f_1$ do 2000-rated players prefer $m_1$?

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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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Last dataset has 10,611 turns with tied-optimal moves. Go back all the way to 1971—when there was no Stockfish 7 program. 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.
Chess and Informatics

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** vigorous . . 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|
| ...    |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
Modeling “Heave”

\[ z_i' = \left( \frac{\delta_i}{s} \right)^c + \left( \frac{h \cdot \rho_i}{s} \right)^{a \cdot c} \]
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- But those fits usually give \( h > 1.5 \), Uh-Oh!
Big Wins for the New Model
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- No longer strictly monotone: Weaker players may prefer weaker moves that look better at early depths, more so if they have higher $h$.
- Separates prediction and performance-assessment components.
- Often accurately predicts inferior moves to be more likely, **But...**
Fine-Grained Trouble Under the Dial

...at the same time it gives near-zero probability to reasonable moves that were played. Even sometimes gives 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 $i$ that allow it to be welded onto the frequency histogram $f_1; f_2; f_3; \ldots$. 
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6. narrative science, and
7. the emergence of new paradigms.

These are our recommendations:

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!