Elements of Extreme Expertise

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Rensselaer Polytechnic Institute

ONR Cognitive Science of Learning Program Review

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Thanks to These Graduate Students

John Lindstedt — Expected to defend his dissertation between Dec 2016 to Feb 2017. Looking for Post-Doc soon!

Catherine Sibert

Matt Sangster
Recent Publications, Presentations, & Awards

Since the last Program Review (October 2015) these papers have been published or are currently accepted and in press:

Three major papers now in press


Conference Papers


- Gray, W. D. and Destefano, M. (2016). Searching not under the lightpole but where we dropped our keys: Using Changepoint Detection to shine the light on periods of strategy invention and change. Paper to be presented at the *57th Annual Meeting of the Psychonomic Society*.

Radio broadcast

Objectives

To identify the elements of extreme expertise required for dynamic task performance!

Tasks Characteristics:
• Require the real-time interaction of a single human with a complex, dynamic decision environment,
• *Where even hesitating requires a decision to hesitate*, and
• Initial performance is poor, but over the course of weeks, months, and years of practice some people achieve mastery and others do not.

Major Objectives:
• Identify the elements
• Identify the changes made in the transition from novice to expert to extreme expert
• Develop methods for identifying elements and changes that generalize to other domains

Tasks such as . . .
Evidence of Generality?

No claims yet for strong generality across domains — however . . .

As our literature review keeps expanding so does our belief that generalizations are emerging.

Example, Reingold and Sheridan (2011) review of the role of eye movements in expertise for chess and medical diagnosis suggest that the “perceptual advantage” of experts in Chess [e.g., de Groot (1946/1965) and Chase and Simon (1973a, 1973b)] is in line with the finding of a global processing advantage is a crucial aspect of visual expertise in medicine (Nodine and Kundel, 1987).

Perceptual Chunking, perceptual learning, perceptual expertise . . . seems to be a common component of expertise in:

• Medical Diagnosis
• Chess
• Tetris
What Makes This Effort Original and Exciting????

We are bringing the rigor and tools of Experimental Psychology to bear on complex task performance.

Games as Experimental Paradigm (GEPs) — supplement, not replace the Experimental Psychology tradition of using Extremely Simple Paradigms (ESPs).

Bringing real-world data into the laboratory by recruit winners of Tetris competitions. Two levels of this . . .
Home Grown
World Class

• and now — we will be collecting data at the ultimate Tetris Tournament!!!

2016
October
22-23

6TH CLASSIC
WORLD CHAMPIONSHIP

OCTOBER 17-18, 2015
PORTLAND RETRO GAMING EXPO
Are we excited? Yes!!! The worst player at last year’s Tournament is 120,000 points better than our best prior player!!!

Bringing real-world data into the laboratory via the use of two levels of real-world Tetris competitions:

1. Sponsored and ran 6 Tetris Tournaments during the Rensselaer Undergraduates annual Genericon—a Games and Anime Festival
2. Identify the changes made in the transition from novice to expert to extreme expert
3. Develop methods for identifying elements and changes that generalize to other domains
Plan for Rest of Talk

- Predicting Tournament Winners via *Principle Component Regression Modeling* — Lindstedt’s work

- Bringing *Machine Learning* methods to bear on understanding human expertise — Sibert’s work

- Summarizing accomplishments
  - Develop methods for identifying elements and changes that generalize to other domains — Plateaus, Dips, and Leaps — Gray & Lindstedt

- & our proposal for Ray’s *Next Big Idea!!*
**Principle Component Regression Modeling**

Main Researcher: John K. Lindstedt (looking for a post-doc)

Expertise and Tetris

- Trained models with players in lab studies
  - quantifying expertise
  - quantifying behavior
  - predicting expertise
- Test models by predicting winners of Tetris Tournaments
**Game Description**

- **Clear 1 line:**
  - 40 points

- **Clear 4 lines:**
  - 1200 points
  - "Tetris!"

**Game 1**

- **“Zoid”**

- **“Pile”**

Score: 118  
Lines: 0  
Level: 0
Feature Decomposition

Basic unit: the “episode”— time from zoid appearing until it is locked into the pile

Approximately 48 measures are extracted or calculated from each episode of play
jaggedness
max_ht
mean_ht
pits
matches
avg_lat
drop_lat
init_lat
translations
rotations

max_ht: 12
pits: 9
mean_ht: 8.1
jaggedness: 21
The complete list of measured features

Could use these to measure player behavior and construct statistical models of player expertise!

Except…
Solution: principal component regression analysis (PCA)
Modeling Tetris Expertise

Constructed 4 models, one model for each of four levels of Tetris play: 0, 1, 5, and 9

- **Level 0**: 1.25 row/s, N = 239 (99%)
- **Level 1**: 1.4 row/s, N = 236 (98%)
- **Level 5**: 2.6 row/s, N = 158 (66%)
- **Level 9**: 10 row/s, N = 27 (11%)
One Player — Different Levels

<table>
<thead>
<tr>
<th>game</th>
<th>score</th>
<th>game data by level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50798</td>
<td>0 1 2 3 4 5 6 7 8 9 10</td>
</tr>
<tr>
<td>2</td>
<td>142443</td>
<td>0 1 2 3 4 5 6 7 8 9 10 11</td>
</tr>
<tr>
<td>3</td>
<td>48650</td>
<td>0 1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>4</td>
<td>106569</td>
<td>0 1 2 3 4 5 6 7 8 9 10 11 12</td>
</tr>
<tr>
<td>5</td>
<td>85028</td>
<td>0 1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>6</td>
<td>178400</td>
<td>0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15</td>
</tr>
<tr>
<td>7</td>
<td>19013</td>
<td>0 1 2 3</td>
</tr>
<tr>
<td>8</td>
<td>8583</td>
<td>0 1 2 3</td>
</tr>
</tbody>
</table>

top 4 mean: 128110 criterion score: 7.1
## PCRM by Levels

<table>
<thead>
<tr>
<th></th>
<th>Level 0</th>
<th>Level 1</th>
<th>Level 5</th>
<th>Level 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. $R^2$</td>
<td>0.626</td>
<td>0.652</td>
<td>0.594</td>
<td>0.491</td>
</tr>
<tr>
<td>df</td>
<td>(5, 232)</td>
<td>(4, 231)</td>
<td>(5, 152)</td>
<td>(3, 23)</td>
</tr>
<tr>
<td>F</td>
<td>80.7</td>
<td>110.9</td>
<td>47.0</td>
<td>9.4</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>4.61</td>
<td>&lt;0.0001</td>
<td>5.01</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>entropy</td>
<td>-0.21</td>
<td>&lt;0.0001</td>
<td>-0.12</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>structure</td>
<td>0.29</td>
<td>&lt;0.0001</td>
<td>0.22</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>fast-fitting</td>
<td>0.47</td>
<td>&lt;0.0001</td>
<td>0.49</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>pivoting/recovery</td>
<td>-0.17</td>
<td>&lt;0.01</td>
<td>-0.10</td>
<td>0.054</td>
</tr>
<tr>
<td>indecision/errors</td>
<td>0.27</td>
<td>&lt;0.01</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>
Modeling Findings

The principal component models successfully differentiate players by skill at all difficulty levels!

Two particularly interesting bits:

- Level 1 gameplay, does best at separating expert behavior
- Expert players *always* exhibit exceedingly fast, accurate movements, even during early levels when it is not needed!

  - *More generalizations??* This sort of physical rehearsal of hand or other movements is reported by researchers in other video games
Model Validation

3 tournaments, at the 2014, 2015, and 2016 Genericon events at RPI. (All using the Meta-T software — Lindstedt & Gray, 2015.)

2 Qualifying games (best of 2) —> ranking in 8-player Tournament bracket
Predicted player’s level of expertise using *only qualifying round data*

- 2 games played under non-lab conditions with some pressure to perform well!

Used best-performing PCA expertise model: Level 1
2014 Tournament

quarter-finals
Q1 → Q8 → Q4 → Q5 → Q6 → Q3 → Q7 → Q2

semi-finals
Q1 → Q5 → Q6 → Q2

runoffs
Q3 → Q2

finals
Q6 → Q1 → Q2 → Q5

Green indicates those predicted to win by the Qualifier score.

big upset!
Q6 → 2nd place
Q1 → 1st place
Q2 → 3rd place
Q5 → runner-up
Tournament Prediction Results

For the 24 tournament matches

- Qualifying rank predicts 58%
- PCR model predicts 83%

PCR model predicts 100% of runoff and final matches; i.e., those that win money

10 matches were upsets (to varying degrees)

- PCR expertise model predicted 70% of them

(PCR model rating over Qualifier rating)

Odds Ratio 3.57
Confidence Interval [0.93, 13.72]
\( p = 0.064 \)
Relatively small slices of player behavior revealed level of expertise (level 1 play!!!)

- Marginal success at rigging tournament bets!

Experts continue to exercise their motor behaviors at near-peak levels, even when not required by the task

- Hints at self-directed practice
Recent Past Work

Main Researcher: Catherine Sibert

# Training a Model to Play Tetris

Trained Cross-Entropy Reinforcement Models* (CERLs) using Dellacherie’s Feature Set

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landing height</td>
<td>Height where the last zoid is added</td>
</tr>
<tr>
<td>Eroded zoid cells</td>
<td># of cells the current zoid eliminated due to line clears</td>
</tr>
<tr>
<td>Row transitions</td>
<td># of full to empty or empty to full, row transitions btw cells on the board</td>
</tr>
<tr>
<td>Column transitions</td>
<td>Same as above for vertical transitions</td>
</tr>
<tr>
<td>Pits</td>
<td># of empty cells covered by at least one full cell</td>
</tr>
<tr>
<td>Wells</td>
<td>A series of empty cells in a column such that their left cells and right cells are both occupied</td>
</tr>
</tbody>
</table>

* Similar to Genetic Algorithms — if that helps!
Best Model Correlations with Human Placements

Proportion of episodes, per player, where model’s best choice matched the player’s actual choice of placements

Proportion Match

Level of Expertise

Score

4Lines

p < 0.00001

Adjusted $R^2 = 0.63$

p < 0.00001

Adjusted $R^2 = 0.60$
What Next for Sibert’s Models?

Anthropogenic Climate Change in Tetris

The Icarus Hypothesis

The Tetris Thunderdome
Model predicted range of goodness value for zoid placements for each episode of Tetris played.
Testing the Icarus Hypothesis

- Our best human game, in the lab, lasted 506 episodes - so we train our “short-run” models for 506 episodes.

- Other models we let run “forever” or until they die — so far the best forever model played for 12,000,000 episodes.

- For reasons we do not fully understand —
  - The best long-run models do not usually beat the short-run models when we stop both at 506 episodes.

- The Icarus Hypothesis — restated: “Icarus’ problem wasn’t that he flew too high but that the ocean was too wide!” (i.e., reason why the 506 models die faster than the “forever” models).

- Or is it that Olympic level marathon runners do not do well running the 100 meters?? (reason why the “forever” models do not usually win at “506” episodes.)
Bring it on!!! The Tetris Thunderdome!!

Inspiration — our best 16 models from a grid search using the MindModeling software are tied exactly on score. How can that be? Is there some sort of optimal in Tetris that the very best models converge at? (The games the models play do NOT asymptote at 999,999 points.)

Take best models from the various methods of model search and pit them against each other

• Cross-entropy reinforcement learning vs MindModeling Grid Searches
  • 4 different objective functions for both

• MindModeling
  • 2 x 2 x 2 factors grid search for optimal parameters
  • 2 Game lengths: 506 episodes versus infinity
  • 2 Magnitudes of feature search
    • -5 to + 5 by 1’s == 11 vs
    • -100 to +100 by factors of 10
      • -100, -10, -1, - 0.1 0, 0.1, +1, +10, +100
  • 2 Random Seeds
Summary — Model Based Approaches

Machine Learning approaches are shedding some unexpected light onto the nature of expertise

• Anthropogenic Climate in Tetris — suboptimal decisions by players lead to a deteriorating spiral in the goodness of the Tetris task environment!

• Icarus Hypothesis — Icarus didn’t err by flying too close to the sun, he erred in underestimating how long it would take to cross the sea!

• The Tetris Thunderdome — defining “optimal play” in Tetris.

Does this shed new light on human expertise??

• How we train our experts? Our extreme experts?

• What our models and our people learn from different approaches to expert training?
No Technical Issues to report

Non-technical or resource issues

• Need for our eye trackers to be portable for field use while maintaining sampling rate of, at least, 250 hz

• Dr. Michael Schoelles stopped active work on this project shortly after last year’s Project Review. He has now officially retired though he plans to maintain a reduced teaching role at Rensselaer and a research role in the CogWorks Lab.
Summarize conclusions resulting from your work to date

- The *Plateaus, Dips, and Leaps* approach provides the intellectual foundation for a new methodological assault on the study of individual and team performance
  - It is in step with the *revisionist power law theorists* — those who argue that within individuals, learning reflects a series of strategies, each of which obeys a power law function
- The *Principle Component Regression Analyses* are showing that Chase & Simon’s (1973) *Perceptual Chunks* are best understood as complex mix of schemas composed of cognitive, perceptual, and action components. (Note that a close reading of CS73 suggests that this description is closer to their original conception that are most modern glosses)
- Results of human decision making in these tasks can be described in terms of *maintaining* or *polluting* the task environment
- The *Icarus Hypothesis* — suggests a new way of understanding human expertise
Cooperative Development

• Rensselaer Presidential Research Fellowship — awarded to Matt Sangster
  • Has enabled us to put Matt on our League of Legends project which is important background work for our new ONR proposal — Expert Blunders and Expert Team Blunders!
  • [This is work with Prof. David Mendonca of Rensselaer’s Industrial Systems Engineering Department. Prof. Mendonca is an expert in Team Performance.]
The concept of *Deliberate Practice* (DP) has had a huge impact on education and training.

- As a very informal survey we did nine Google searches using the term “deliberate practice + [term]; where “+ [term]” was “teacher,” “golf,” “skiing,” “frisbee,” “marathon,” “poker,” “mathematics,” and “second language learning.” All produced thousands to millions of hits that when spot checked (from those returned on the first page of results) showed a preponderance of pages talking about the use of DP in that field.

- We see our work as impacting the development of DP for extreme expertise in skills that entail real-time, dynamic decision making, with a significant perceptual motor component. Recently we have begun researching the literature in the fields of medical diagnosis and surgery to determine possible paths forward in those domains.
  - In pursuit of these questions we have been in contact with Program Officers at the National Cancer Institute.

- However, although we believe our work will be transformative, we also believe that the first batch of papers has just started to confirm our claim on this field.

- We have succeeded, to this point, by being able to obtain millisecond level performance data on cognitive, perceptual, and motor events and apply advanced statistical and modeling techniques to these data. We strongly believe, that a second round of ONR 6.1 funding will enable us to put this emerging area onto a firm theoretical, quantitative, and methodological footing.
Anyone can make a mistake — but it takes an expert to really blunder! (i.e., experts should know better but still make mistakes! what’s with that???)

- Can these be avoided? Maybe, sometimes, perhaps by . . .
  - Disaster Avoidance Planning and
  - Disaster Recovery Planning
- And do we have a great proposal, on this very topic, for ONR?? Yup!!
- Title: Bad Choices!! Using Big, Long, and Multivariate Data to Explore Blunders Made by Teams and Individuals, Experts and Novices in Dynamic Skilled Performances
- See also Robert Pokorny’s talk and discussion of mistakes made by technicians