Elements of Extreme Expertise

Searching for Differences in Microstrategies Deployed by Experts and Novices

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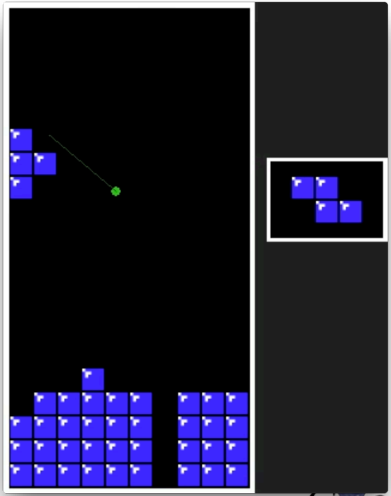
Outline

1. Everyone Knows Tetris®
2. Infrastructure
3. Overview of the Full Project
   - Finding Players
   - What are Players Optimizing? Machine Learning Approach
   - Increasing Expertise(?)
4. The Eyes Have It! (Focus of the Rest of this Talk)
   - Can Expertise be Recovered from the TMs??
   - Within Player Changes in Strategy with Level
5. Summary: Much Work Remains

EVERYONE KNOWS TETRIS®

The movie for this slide has been uploaded to youTube: Tetris game with point-of-gaze – click here to watch.



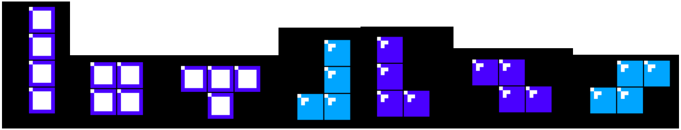
- Clearing 40 lines in under 20 sec at an average rate of 4 pieces/sec!!

  - Clearing 40 lines in under 20 sec at an average rate of 4 pieces per sec!!
  - Interview with Jono Pearson (see especially 1:30 and after)

Note that, rather than relying on internet connectivity, the KogWis14 presentation used a downloaded version of these videos with one video on each of two successive pages.

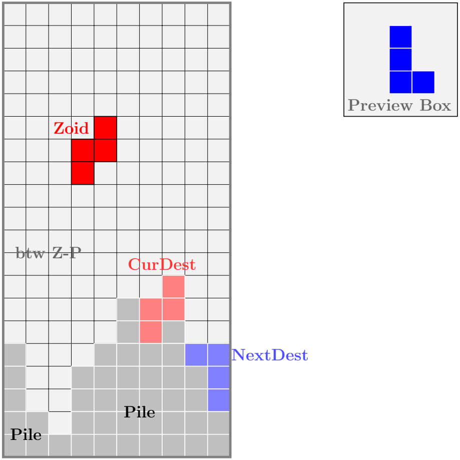
TETRIS TERMINOLOGY

- *Zoids*
  - The Tetris pieces are called *zoids*.
  - All zoids are composed of four square blocks
  - There are seven (7) different zoids which are commonly called the: I, Square, T, J, L, Z, and S.



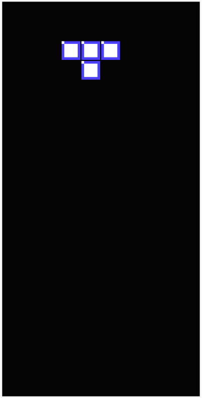
TETRIS TERMINOLOGY (cont'd)

- The Tetris board is 10 squares wide and 20 squares high.
- One zoid drops at a time.
- After it hits the *pile* it stops moving and becomes part of the *pile*.
- You gain points by *clearing rows*. Rows clear when all 10 squares in the row are filled by zoid-squares.



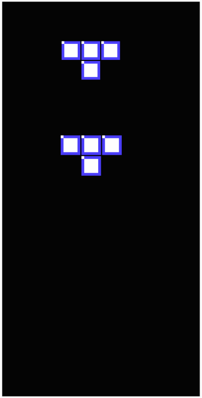
Pressure

Level 1



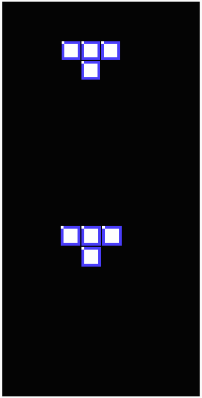
1.25 rows/ second

Level 5



2.6 rows/ second

Level 9



10 rows/ second

TETRIS TERMINOLOGY (cont'd)

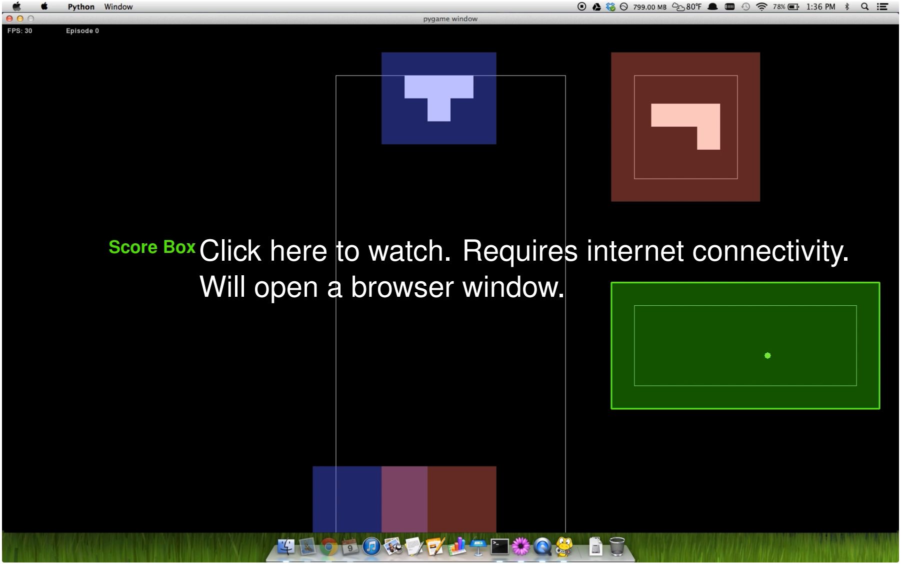
- Points multiply when you clear multiple rows at once.
- Points for clearing rows also multiply as the level (i.e., speed) of play increases.

Points per line cleared	1 Line	2 Lines	3 Lines	4 Lines
Level 01	40	100	300	1200
Level 20	800	2000	6000	24000

- Games may be the one form of daily behavior that satisfy the demands of *rational adaptation* theorists; that is,

> *"to narrow the space of predicted behaviors through analysis of the payoff achieved by alternative strategies, rather than through fitting strategies and theoretical parameters to data."*
> *Howes, Lewis, and Vera (2009)*

- How can we bring Tetris into the lab and why would we want to?



A CHALLENGE TO COGNITIVE SCIENCE(?)

- What we see when we look:
  - Cognitive control
    - switching among the substeps required to
    - monitor,
    - guide, and
    - place the current zoid while
    - planning the placement of the next zoid
  - Actions that we see for the current zoid suggest the
    - dynamic adjustment of placement plans
    - a continual evaluation of the pile
    - and some sense that these experts have that we do not yet have of strategic goals and tactics for Tetris

TETRIS® AS A *REAL WORLD* TASK

- People play Tetris outside the laboratory (a lot!!)
- Entails tight loop between cognition, action, and perception in a dynamic task environment
- Requires real-time dynamic decision making
- Games, such as Tetris, should enable us to “narrow the space of predicted behaviors through analysis of the payoff achieved by alternative strategies.”

OUR GOAL . . .

To build the Cognitive Science theories that generalize beyond games – to other tasks involving real-time interaction of a single human with a complex, dynamic decision environment.

With Tetris as our testbed, can we develop techniques to explore . . .

1. *Expert Performance*
2. *Expert Development*
3. *Expert Instruction*

Can we turn *mere* Experts into *Extreme* Experts???

OUR CAVEAT . . .

- Current focus:
  - Understanding what the cognitive, perceptual, and motor pieces of performance are and how they fit together.
  - Harvesting detailed data from a wide skill range of Tetris Players.

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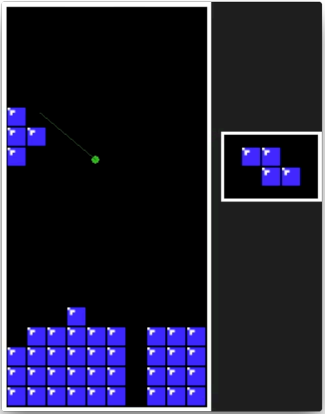
MINIMUM OF 60 RESEARCH PAPERS THAT USED TETRIS

"Tetris is the most studied spatial puzzle game", (Mayer, 2014, p. 178). But, how many of these studies looked at what the players were doing…

This is a trick question, the answer is ZERO!!

- No one looked at what the players were looking at!!
- Most limited themselves to using the information visible and available to players – levels played, lines cleared, total score)



MetaT: Tetris® as Experimental Paradigm

- Tetris: Commercial game – inaccessible to experimental manipulation or detailed data analysis.
- MetaT: Research tool – designed and written with data collection and experimental manipulation in mind.
- Lindstedt and Gray (accepted pending final changes)

MetaT - *Some of* What We Log ...

From the Appendix B of Lindstedt and Gray (accepted pending final changes)

General outputs
ts - time stamp in seconds since the beginning of the session
event_type - designates the type of entry this row represents in the log
SID - the Subject ID
ECID - the Experimental Condition ID
session - the date and time of the start of the session
game_type - the game type label
episode_number - the number of the current episode this game
lines_cleared - the number of lines cleared this game
tetrises_game - number of tetrises scored this game

Game summary outputs
completed - whether or not a game was completed or terminated early (manually or by failure)
game_duration - length in seconds of the game
avg_ep_duration - length of the average episode this game
zoid_sequence - the exact sequence of zoids seen this game (of the types I, O, T, S, Z, J, and L)

Immediate event outputs
evt_id - the ID of the current event. This is highly flexible and depends on the event.
evt_data1 - the first value of the current event. depends heavily on evt_id. evt_data2 - the second value of the current event. depends heavily on evt_id.

Game state outputs
curr_zoid - the current zoid this episode (of I, O, T, S, Z, J, and L)
next_zoid - the upcoming zoid for the next episode (of I, O, T, S, Z, J, and L)
delaying - whether the game is currently delaying, waiting for a new zoid to appear
dropping - whether the player is currently dropping the zoid
zoid_rot - current rotation of the zoid (between 0 and 3 for T, J, and L; 0 and 1 for I, S, and Z; 0 for O)
zoid_col - current column of the upperleft-most square of the zoid's bounding box
board_rep - exact visual representation of the pile (without the current zoid)
zoid_rep - exact visual representation of the zoid's current position.

Episode summary outputs
evt_sequence - sequences of keypresses and events taken this episode.
rots - number of rotations performed
trans - number of translation (left or right) performed
u_drops - number of rows the zoid traversed due to player dropping
s_drops - number of rows traversed by the zoid due to system gravity
initial_lat - latency in milliseconds of the first keypress in an episode
drop_lat - latency in milliseconds until zoid is dropped in an episode
avg_lat - average latency between keypresses this episode

MetaT - *SOME OF* WHAT WE CAN MANIPULATE . . .

From the Appendix B of Lindstedt and Gray (accepted pending final changes)

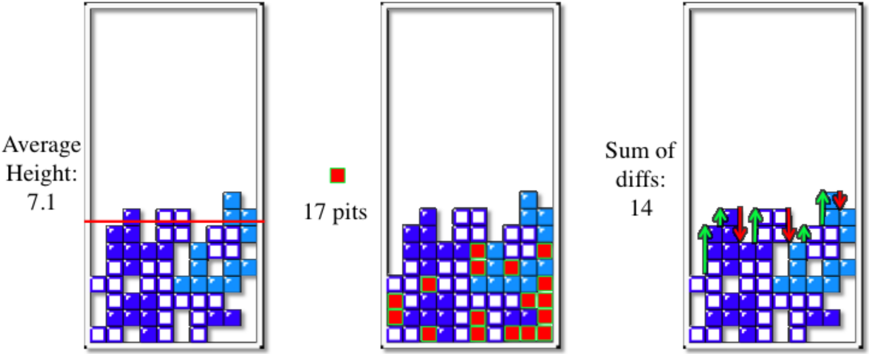
```
#FIXED parameters (listed in each config file)

#Presentation
fullscreen = true
music_vol = 0.0

#Randomization
fixed_seeds = true
random_seeds = 1, 2, 3, 4, 5
permute_seeds = true

#Game length
continues = 5
max_eps = 100

#Game difficulty
starting_level = 4
lines_per_lvl = 9000

#Player actions allowed
pause_enabled = false
```

```
#VARIED parameters -- GUIDED CONDITION
# Experiment and Condition ID
ECID = E1_GDD ## abbreviation of "guided"

ghost_zoid = true
gridlines_x = true
gridlines_y = true

#VARIED parameters  -- NOT-GUIDED CONDITION
# Experiment and Condition ID
ECID = E1_notGDD ## abbreviation for "not guided"

# The next three settings are the default MetaTetr
# parameters. Hence, they could be omitted. Howeve
# to explicitly document the setting of key parame

ghost_zoid = false
gridlines_x = false
gridlines_y = false
```

METRICS: “How good was that last move?”

Example of 3 out of $\approx$ 30 metrics.

Mean height of game board | **Number of Pits** | **“Length” of the top ridge**



Lindstedt and Gray (2013)

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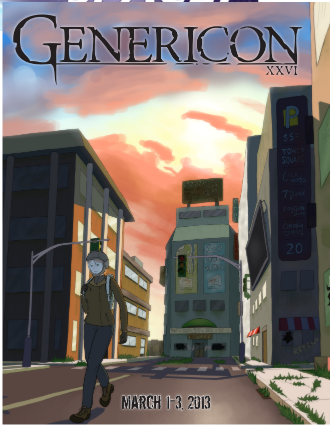
SCREENING FOR EXPERTISE: TETRIS TOURNAMENTS



SCREENING FOR EXPERTISE – in lab studies

In lab manipulation of game elements (using MetaT):

- All empirical studies begin with one hr of *free play* – have accumulated $\approx$ 80 hours of Tetris free play this way.
- This semester, we will screen $\approx$ 200 – 300 Psychology 100 students. Searching for Extreme Expertise and helping to provide matched subjects for planned studies.

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MOVE-BY-MOVE

Question: How can we judge the *goodness* of each move as it is made?

- Multiple Regression approach: Indicated that as few as ten successive episodes (i.e., Zoid placements), enabled us to classify players as Novice or Expert.
- *Cross-Entropy Reinforcement Learning* techniques – similar to Genetic Algorithms.

Lindstedt and Gray (2013)
Siberts, Lindstedt, and Gray (2014)

Tetris from the Perspective of Artificial Intelligence

- Tetris is a benchmark problem in AI, as it is known to be computationally hard to solve.
- A huge number of board configurations: 2^{200} (about 10^{59})!!
- Finding the strategy that maximizes the average score is an NP-complete problem.

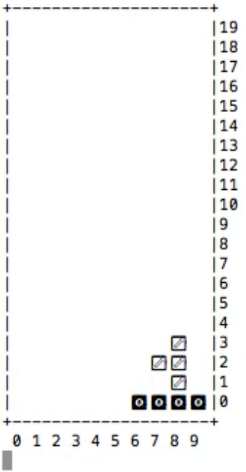
Thiery and Scherrer (2009)

How to Build a Cross-Entropy RL Tetris Player

Table: Sample Features Proposed for Tetris by Dellacherie

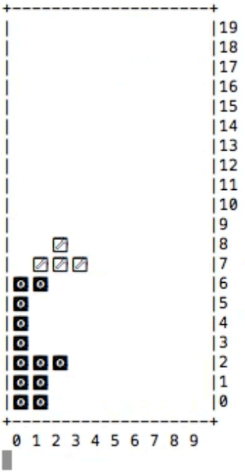
Feature	C1	C2	Description	Comments
Landing height	-1	+1	Height where the last piece is added	Prevents from increasing the pile height
Eroded piece cells	+1	+1	(Number of rows eliminated in the last move) x (Number of bricks eliminated from the last piece added)	Encourages to complete rows
Row transi-tions	-1	-1	Number of horizontal full to empty or empty to full transitions between the cells on the board	Makes the board homogeneous
Column transi-tions	-1	-1	Same thing for vertical transitions	
Holes	-4	+1	Number of empty cells covered by at least one full cell	Prevents from making holes
Board wells	-1	-1	A well is a succession of unoccupied cells in a column such as their left cells and right cells are both occupied	Prevents from making wells

Slow Dellacherie C1



Dellacherie C1

Idiotic-Dellacherie C2



DIFFERENCES ACROSS MODELS?

Major differences

- Compared two features sets:
  - Superset of 48 feature: *The Lindstedt 48*.
  - Set reported in AI literature of 6 features: *The Dellacherie 6* (Fahey, 2013).
- Varied 4 Objective Functions – what the model is rewarded for doing.
  - Total Score
  - Number of Lines Cleared
  - Highest Level achieved
  - Number of Tetrises per game

CAN CERLS PREDICT HUMAN CHOICE?

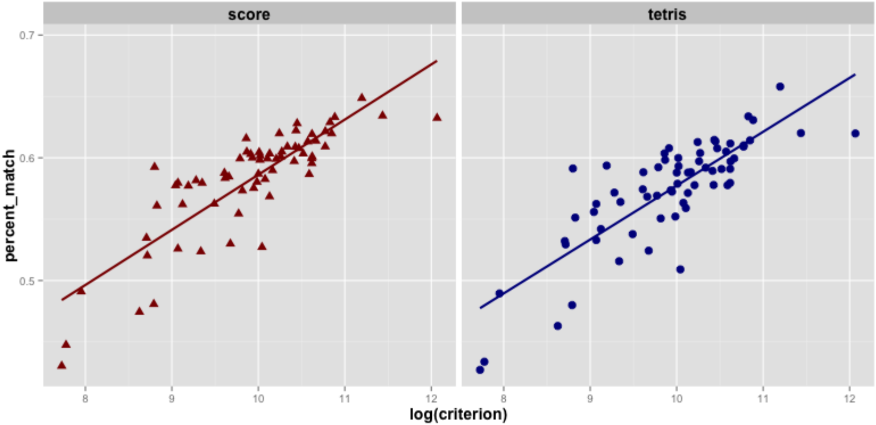
- Will novices be easier to predict than experts? (Experts have more higher level strategies . . .) but novices seem less rule-based.
- Which Objective Function will do the best?
  - Total Score? Lines Cleared? Number of Tetrises? Highest Level of play?
- Which Feature Set?
  - *The Lindstedt 48* or *Dellacheire 6*?

WINNOWING THE MODELS

- From considerations of efficiency (Akaike's Information Criterion - AIC)
  - We first rejected all 4 of the Lindstedt 48.
  - Then rejected two objective functions.

AND THE WINNERS ARE!

Feature Set: The Dellacherie 6.
Objective Functions: Score and Number of Tetrises



Surprise?? CERLs predict expert choices much better than they do novice choices.

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NEXT STEPS – CERLS

- Can CERLS be used in real-time tutoring of Tetris?
- Several ideas for how this might be implemented will be tested this Fall for C. Siberts' Masters Thesis.

NEXT STEPS – EXPERIMENTAL STUDIES

- Spring 2014: Completed 6-hr study – 4 groups, across 4 90-min sessions
- Spring 2015: Follow-on studies planned – also involving 4 90-min sessions.

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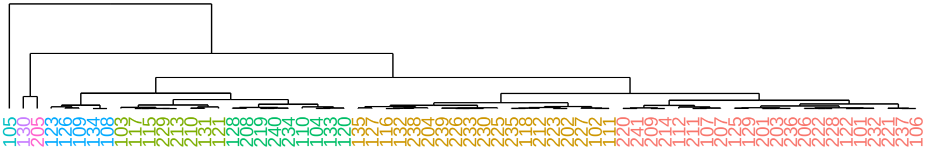
FIRST – DID WE FIND ANY EXPERTS OR EXTREME EXPERTS?

- hclus() analysis told to divide the players into 8 skill-based groups.
- Best solution found 3 one-person groups – one each for our highest three performers!
- Here we present data from these two groups.



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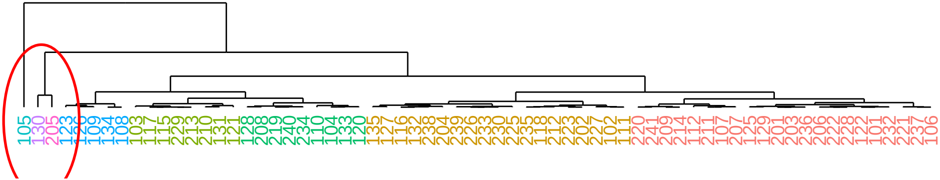

- YES!! WE DID!!!

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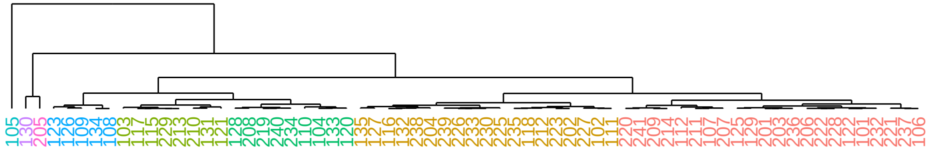

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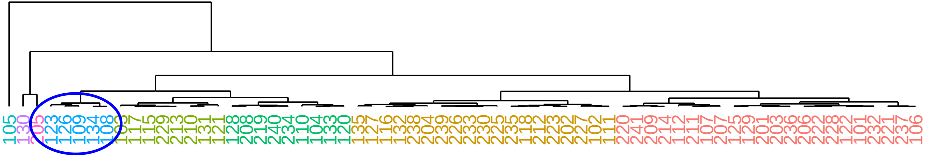

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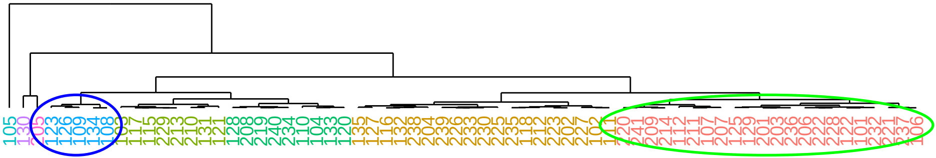
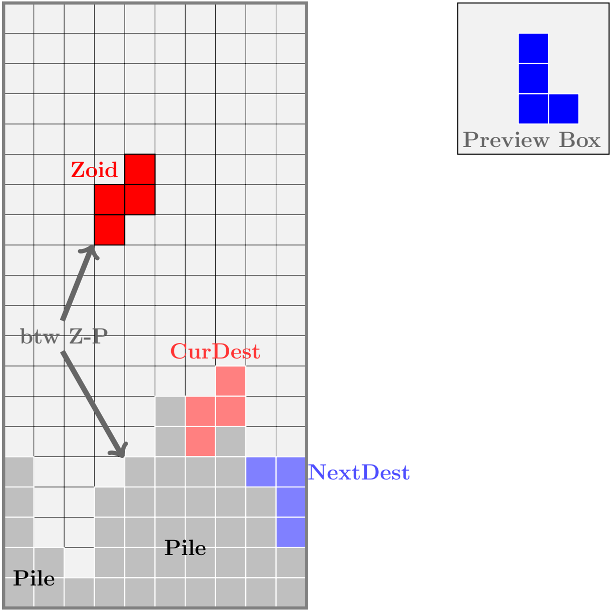


TETRIS AREAS OF INTEREST (6 ROIs)



THE EYES HAVE IT!

- 34,327 fixations from 4 games of Tetris for 6 Novices and 5 Experts.
- Base Model: Transitions btw *Regions of Interest* (ROIs) simply reflect the probabilities that an ROI is fixated.
- **green** indicates ***more*** while **brown** indicates ***fewer*** than expected by Base Model.
- z-score plot ($+/-$ 2.6 would be a two-sided probability of $p < .01$)

PAIRWISE TRANSITION MATRIX – Adjusted Residuals

- Base Model: transitions are proportional to the overall rate that an ROI is fixated; the ROI of the prior fixation should NOT matter!!

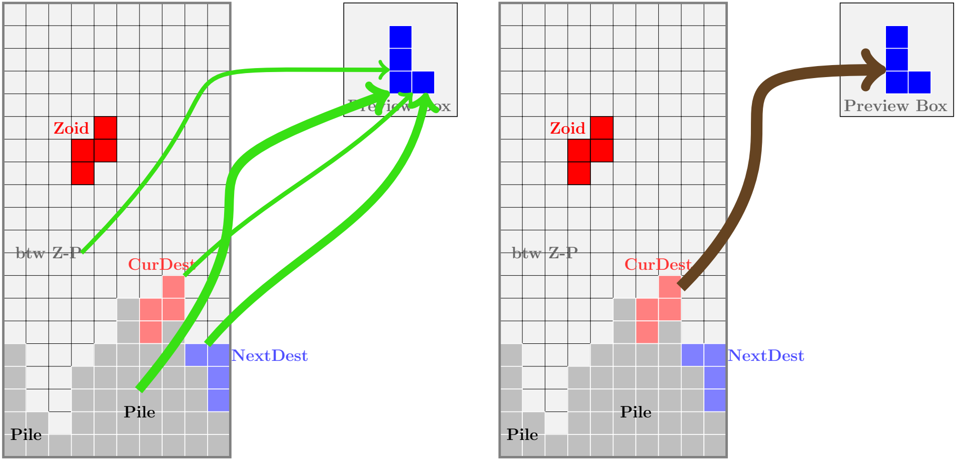
From / To	PBox	BTW	Zoid	CurDest	NextDest	Pile
EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT
PBox	0.0	-0.8	**-4.5**	0.8	**12.9**	**12.5**
BTW	**3.5**	0.0	**3.7**	**-3.9**	–2.1	1.1
Zoid	-0.4	**-11.3**	0.0	–1.5	**-3.4**	**-3.4**
CurDest	**3.4**	**4.4**	–2.2	0.0	**-4.1**	–2.0
NextDest	**6.1**	**7.9**	**-5.4**	–1.1	0.0	**12.0**
Pile	**7.0**	**13.4**	**-9.3**	2.2	**13.1**	0.0
NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE
PBox	0.00	-2.3	**-8.3**	**-6.4**	**3.1**	**5.5**
BTW	-1.8	0.0	**4.6**	**-7.0**	**-2.6**	–1.4
Zoid	-1.7	**-3.3**	0.0	**10.6**	0.6	2.2
CurDest	**-8.8**	-1.6	**13.6**	0.0	**-10.8**	**-12.8**
NextDest	-1.2	0.1	**-3.0**	**-4.1**	0.0	–0.2
Pile	-2.1	2.3	–1.5	**-6.8**	0.6	0.0

TRANSITIONS TO THE PREVIEW BOX

- What differences between strategies used by experts vs novices are suggested by the *Adjusted Residual Matrix*??

From / To	PBox	BTW	Zoid	CurDest	NextDest	Pile
EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT
PBox	0.0	-0.8	-4.5	0.8	12.9	12.5
BTW	3.5	0.0	3.7	-3.9	–2.1	1.1
Zoid	-0.4	-11.3	0.0	–1.5	-3.4	-3.4
CurDest	3.4	4.4	–2.2	0.0	-4.1	–2.0
NextDest	6.1	7.9	-5.4	–1.1	0.0	12.0
Pile	7.0	13.4	-9.3	2.2	13.1	0.0
NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE
PBox	0.00	-2.3	-8.3	-6.4	3.1	5.5
BTW	-1.8	0.0	4.6	-7.0	-2.6	–1.4
Zoid	-1.7	-3.3	0.0	10.6	0.6	2.2
CurDest	-8.8	-1.6	13.6	0.0	-10.8	-12.8
NextDest	-1.2	0.1	-3.0	-4.1	0.0	–0.2
Pile	-2.1	2.3	–1.5	-6.8	0.6	0.0

TRANSITIONS TO THE PREVIEW BOX (or not!)



Expert

Novice

More Likely Than Expected

Less Likely Than Expected

TRANSITIONS TO THE ZOID

- What differences between strategies used by experts vs novices are suggested by the *Adjusted Residual Matrix*??

From / To	PBox	BTW	Zoid	CurDest	NextDest	Pile
EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT
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BTW	3.5	0.0	3.7	-3.9	–2.1	1.1
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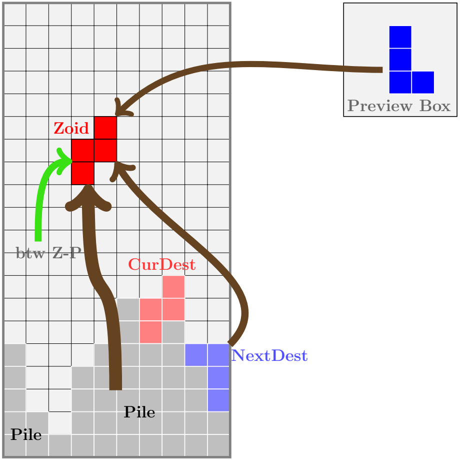
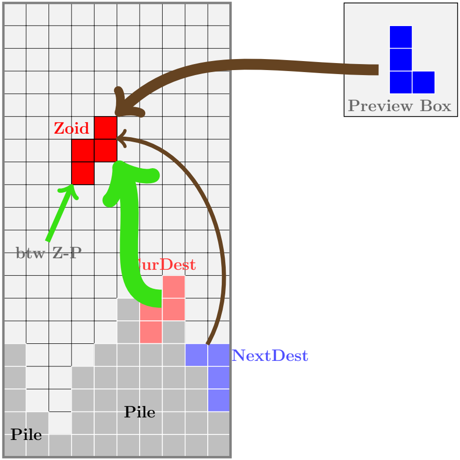
NextDest	6.1	7.9	-5.4	–1.1	0.0	12.0
Pile	7.0	13.4	-9.3	2.2	13.1	0.0
NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE
PBox	0.00	-2.3	-8.3	-6.4	3.1	5.5
BTW	-1.8	0.0	4.6	-7.0	-2.6	–1.4
Zoid	-1.7	-3.3	0.0	10.6	0.6	2.2
CurDest	-8.8	-1.6	13.6	0.0	-10.8	-12.8
NextDest	-1.2	0.1	-3.0	-4.1	0.0	–0.2
Pile	-2.1	2.3	–1.5	-6.8	0.6	0.0

TRANSITIONS TO THE ZOID (or not)



Expert



Novice

More Likely Than Expected

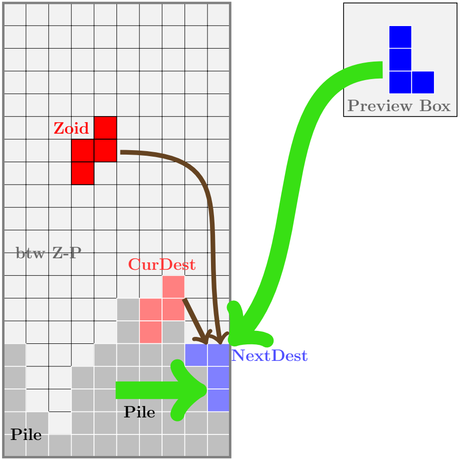
Less Likely Than Expected

TRANSITIONS TO THE NextDest

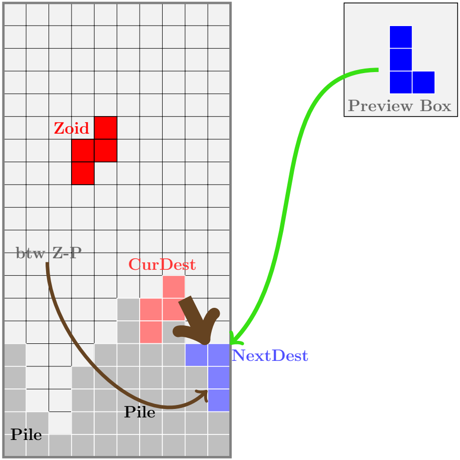
- What differences between strategies used by experts vs novices are suggested by the *Adjusted Residual Matrix*??

From / To	PBox	BTW	Zoid	CurDest	NextDest	Pile
EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT	EXPERT
PBox	0.0	-0.8	-4.5	0.8	12.9	12.5
BTW	3.5	0.0	3.7	-3.9	−2.1	1.1
Zoid	-0.4	-11.3	0.0	−1.5	-3.4	-3.4
CurDest	3.4	4.4	−2.2	0.0	-4.1	−2.0
NextDest	6.1	7.9	-5.4	−1.1	0.0	12.0
Pile	7.0	13.4	-9.3	2.2	13.1	0.0
NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE	NOVICE
PBox	0.00	-2.3	-8.3	-6.4	3.1	5.5
BTW	-1.8	0.0	4.6	-7.0	-2.6	−1.4
Zoid	-1.7	-3.3	0.0	10.6	0.6	2.2
CurDest	-8.8	-1.6	13.6	0.0	-10.8	-12.8
NextDest	-1.2	0.1	-3.0	-4.1	0.0	−0.2
Pile	-2.1	2.3	−1.5	-6.8	0.6	0.0

TRANSITIONS TO THE NEXTDEST (or not)



Expert



Novice

More Likely Than Expected

Less Likely Than Expected

SUMMARY – WHAT PATTERNS DO WE FIND?

Differences between Expert and Novice Tetris players in their ...

- Transitions to the Preview Box
- Transitions to the area Between the Zoid and the Pile
- Transitions to the Zoid
- Transitions to the Destination of the next Zoid (NextDest)

Beyond simply "finding differences" we are finding *meaningful differences* that can be interpreted in terms of differences in the strategies and microstrategies used by Experts and Novices.

Outline

1 Everyone Knows Tetris®

2 Infrastructure

3 Overview of the Full Project
- Finding Players
- What are Players Optimizing? Machine Learning Approach
- Increasing Expertise(?)

4 The Eyes Have It! (Focus of the Rest of this Talk)
- Can Expertise be Recovered from the TMs??
- Within Player Changes in Strategy with Level

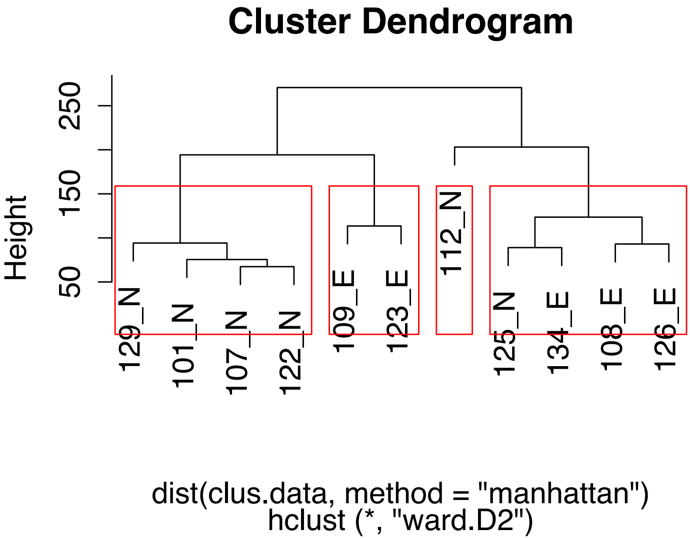
5 Summary: Much Work Remains

CogWorks

CAN EXPERTISE BE CLASSIFED FROM THE TRANSITION MATRICES?

- For calculated each Player's transition matrix and converted this into a vector.
- We fed these 11 vectors into the "dist" and the "hclus" algorithms (as implemented in R).
- Question: Will Player's cluster by level of expertise?
- ???

A TEST OF OUR FINDINGS: CAN EXPERTISE BE CLASSIFED FROM TMs?



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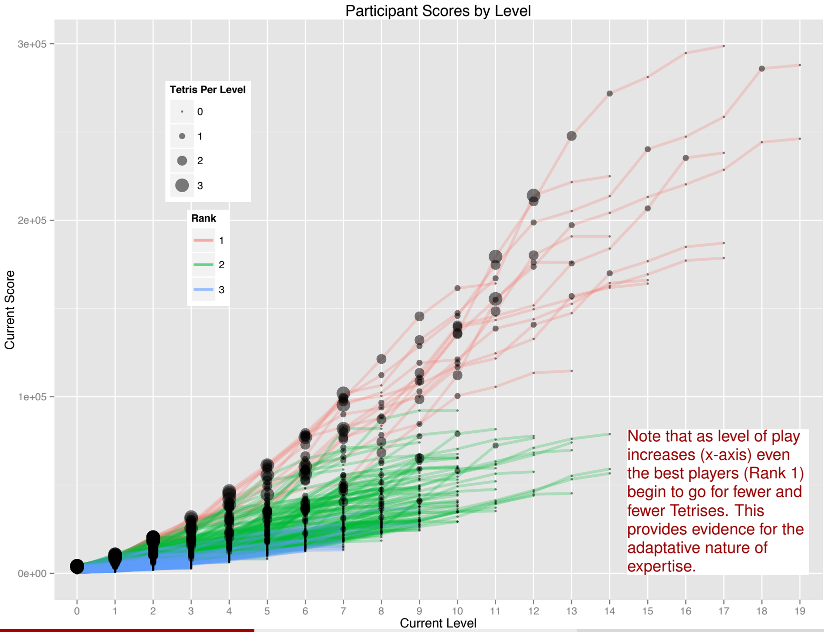
TETRISES BY PLAYER BY GAME LEVEL



Note that as level of play increases (x-axis) even the best players (Rank 1) begin to go for fewer and fewer Tetrises. This provides evidence for the adaptative nature of expertise.

Outline

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CURRENT LIMITS

- *ISO* Extreme Experts
  - Hard to find.
  - Our initial sample of 80 suggests we have found, possibly, three.
- How to get more . . . ??
  - Attempting this semester to run as many as possible (800 possible) Psychology 100 students through an hour of MetaT.
  - Continue sponsoring MetaT tournaments for Tetris Players.
  - Longitudinal studies: In the spirit of the Ericsson, Chase, and Faloon (1980) studies on digit span.

MUCH WORK REMAINS . . .

- Science
  - Test and validate these apparent distinctions
  - We need to integrate the keystroke data and event data into our transition matrix analyses to obtain a more complete picture of expert vs novice strategy differences.
  - Look at differences for Experts at different levels of game play
    - Rational Adaptation theory suggests that to stay in the game our experts should be using different strategies as the game speeds up.
  - Search for differences in transitions between EXTREME Experts and Experts
  - Search for transitional strategies between novices and intermediate levels of players

MUCH WORK REMAINS . . .

- Application
  - Knowing the microstrategies and strategies of experts, and knowing how they differ from novice microstrategies and strategies, can we design training that will hasten the transition from novice to expertise in this task?
  - & will what we have learned here help us understand and improve training for other real-time, interactive, design-making tasks such as laparascopic surgery, air traffic control, etc?

Can we turn *mere* Experts into *Extreme* Experts???


Vielen Dank!

REFERENCES I

Ericsson, K. A., Chase, W. G., & Faloon, S. (1980). Acquisition of a memory skill. *Science*, *208*(4448), 1181–1182.

Fahey, C. P. (2013). *Tetris AI*.

Howes, A., Lewis, R. L., & Vera, A. (2009). Rational Adaptation Under Task and Processing Constraints: Implications for Testing Theories of Cognition and Action. *Psychological Review*, *116*(4), 717–751.

Lindstedt, J. K. & Gray, W. D. (2013). Extreme expertise: Exploring expert behavior in Tetris. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of the 35th Annual Meeting of the Cognitive Science Society* (pp. 912–917). Austin, TX: Cognitive Science Society.

Lindstedt, J. K. & Gray, W. D. (accepted pending final changes). MetaTetris: Tetris as an Experimental Paradigm for Cognitive Skills Research. *Behavior Research Methods*.

REFERENCES II

Mayer, R. E. (2014). *Computer games for learning: an evidence-based approach*. Cambridge, MA: MIT Press.

Siberts, C., Lindstedt, J. K., & Gray, W. D. (2014). Tetris: exploring human strategies via cross entropy reinforcement learning models. In P. Bello, M. Guarini, M. McShane, & B. Scassellati (Eds.), *Proceedings of the 36th Annual Conference of the Cognitive Science Society*. Austin, TX: Cognitive Science Society.

Thiery, C. & Scherrer, B. (2009). Improvements on learning Tetris with cross-entropy. *ICGA Journal*, *32*(1), 23–33.