

# The Essence of Interaction in Boundedly Complex, Dynamic Task Environments

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## Abstract

Studying the essence of interaction requires task environments in which changes may arise due to the nature of the environment or the actions of agents in that environment. In dynamic environments, the agent's choice to do nothing does not stop the task environment from changing. Likewise, making a decision in such environments does not mean that the best decision, based on current information, will remain "best" as the task environment changes. This chapter summarizes work in progress which brings the tools of experimental psychology, machine learning, and advanced statistical analyses to bear on understanding the complexity of interactive performance in complex tasks involving single or multiple interactive agents in dynamic environments.

## Introduction

The shape of a gelatin dessert cannot be predicted from the properties of gelatin, but from the shape of the mold into which it was poured. If people were perfectly adaptable, psychology would need only to study the environments in which behavior takes place (Simon 1992:156).

[B]ehavior cannot be predicted from optimality criteria alone without information about the strategies and knowledge agents possess and their capabilities for augmenting strategies and knowledge by discovery or instruction (Simon 1992:157).

Auch zum Zögern muß man sich entschließen. [Even the hesitation you have to decide.] (Lec 1962)

Simon had it easy. Much of the world he studied moved in discrete steps, as in the Tower of Hanoi (Anzai and Simon 1979; Simon 1975, 1989) or Chess (Gobet and Simon 1996; Simon 1989; Simon and Chase 1973; Simon and Gilmartin 1973). In choosing such tasks, he revealed to us the foundation on which cognitive science could be built and forced us to consider not just the world in our head, but how the capabilities and capacities in our heads were shaped by the mold of the world in which we found ourselves.

The gelatin mold analogy that Simon so liked leads us, perhaps unwittingly, to think of the world as static and ourselves (and maybe the next generation of our creations) as the only active agents. Yet if we stop for too long, it will rain and we will be forced to seek shelter. If we keep working hard, we will become tired and hungry and need to seek food and a place to rest. Indeed, perhaps we are less proactive and more reactive to changes in our task environments than we would like to believe.

In this chapter, we discuss our recent work with single and multiple agents seeking to accomplish complex tasks through a series of sequential choices made in dynamic task environments. In all cases, the choices are presented by an active task environment and the goal is to use our cleverness to deal with that environment and survive as long as possible. In all cases, even doing nothing requires a decision to do nothing.

Although many of the other chapters in this volume discuss humans interacting with robots, or the more general framework of two interacting agents learning from each other (Mitchell et al., this volume), we see the essence of interaction as not defined primarily by biology (or the lack thereof) or agency. Instead, we propose that the essence of interaction lies at the intersection of (a) the skills and abilities of one or more individual agents, (b) the definition of the task, and (c) the nature of change in autonomously dynamic task environments. A key point of emphasis is that intelligent agents learn from interaction with their environments just as they do from each other. The examples in this chapter serve to highlight this insight and its importance in a broader conceptualization of interactive task learning (ITL).

## Background

It seems to me therefore that mental training in schools, in industry and in morals is characterized, over and over and over again, by *spurious limits*—by levels or plateaus of efficiency which could be surpassed. The person who remains on such a level may have more important things to do than to rise above it; the rise, in and of itself, may not be worth the time required; the person's nature may be such that he truly cannot improve further, because he cannot care enough about

the improvement or cannot understand the methods necessary. But sheer absolute restraint—because the mechanism for the function itself is working as well as it possibly can work—is rare. (Thorndike 1913:181)

The task environment and the properties of the human cognitive, perceptual, and motor systems act as soft constraints on human behavior (Gray et al. 2006). With all else equal, the human cognitive system tends to select the fastest way it can to get a job done, with the result that no one modality is privileged and the mix of methods selected are sensitive to the burden placed on cognitive, perceptual, and motor components of human cognition. However, nothing is simple about human cognition. Once a method is acquired and used, it receives the benefits of knowledge compilation (Anderson 1987), which may make it faster and more efficient than a newer but unpracticed (and thereby “uncompiled”) method even though, with practice, the efficiency of the newer method would surpass the old. Unfortunately, this is a fairly common, human situation. If the unpracticed new method is slower or otherwise less efficient than the compiled older method then, as Thorndike observed, it can be exceedingly difficult to entice people to “care enough about the improvement” to put in the time and energy needed to acquire the more efficient method.

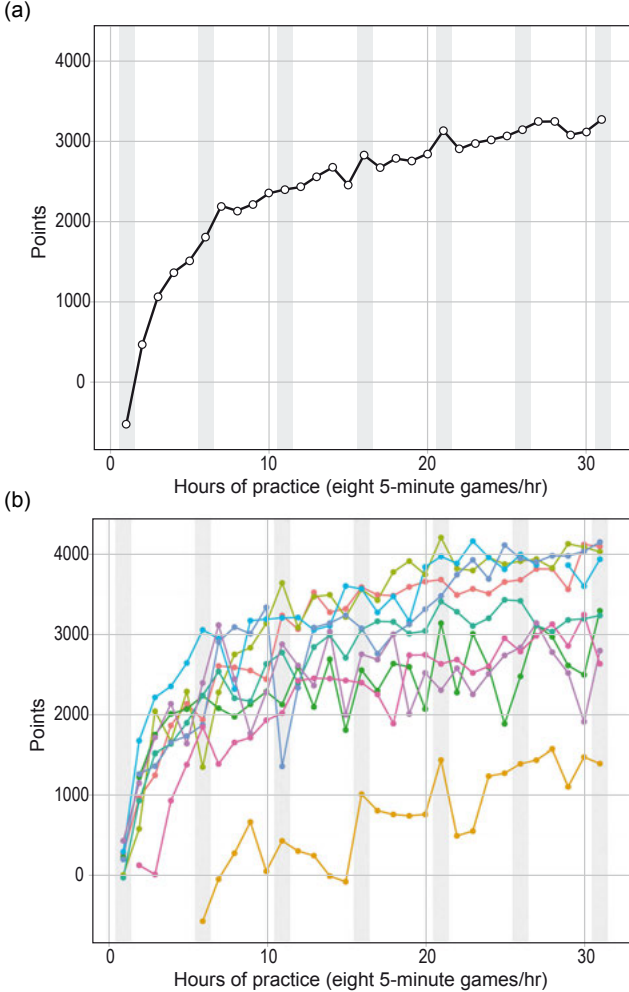
A sterling example of this is the time and effort that people who are visually guided typists (a.k.a. “hunt and peck,” “eagle fingered”) need to spend if they wish to become touch typists. Indeed, the arduousness of this transition, together with the drop in performance while learning the new method, is the main source of recidivism (Yechiam et al. 2003). This pattern of an “easy” but suboptimal method interfering with the acquisition of an initially more difficult, but ultimately faster method has also been shown to be the case for people who first acquire simple menu-based methods for computer-based tasks and are then taught faster scripting-based methods (Cockburn et al. 2014; Yechiam et al. 2004). Fu and Gray (2004) coined the term “stable suboptimal performance” in the context of a study in which an expert architect was shown to have imposed the sequence of steps from his long-established paper and pencil drafting practices onto his current architectural CAD/CAM system.

Our recent work builds on the *soft constraints hypothesis* (Gray et al. 2006) and the concept of *stable suboptimal performance* (Fu and Gray 2004) to explore the elements of extreme expertise in complex, interactive behavior in dynamic task environments.

### **Framing the Work: Plateaus, Dips, and Leaps**

In studying the behavior of people who become expert performers, we must look beyond group measures and focus on the behavior of individuals; that is, at their explorations, failures, and successes as they strive to become experts. For example, we (Destefano 2010; Destefano and Gray 2008) had people play the complex game of *Space Fortress* (Donchin 1995; Mané and Donchin 1989)

across 31 sessions of 8 games per session (248 games total). Averaging the data across hours and across players produces the classic performance curve shown in Figure 10.1a: with few exceptions (Anderson 1987; Fitts 1964; Newell and Rosenbloom 1981), performance improves steadily with practice. Unfortunately, as shown in Figure 10.1b, this smooth average represents no player's actual performance. Although each of our 9 players shows improvements over time, these improvements are not smooth: each individual curve is



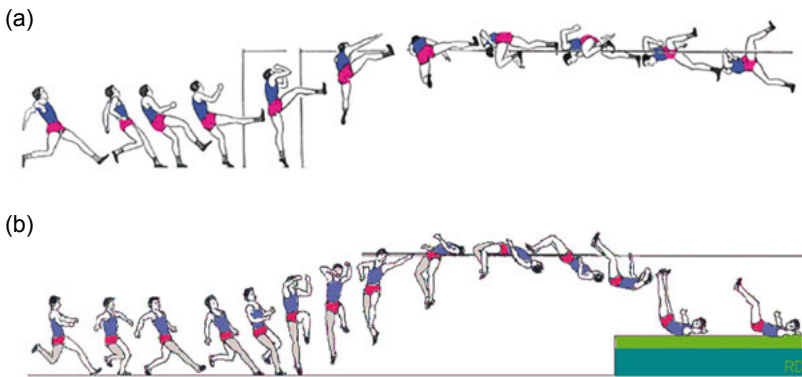
**Figure 10.1** *Space Fortress* skill acquisition curves. (a) Mean performance per hour for all 9 players across 31 hr. (b) Actual scores for each individual player. To keep the plots compact, the early games for the lowest scoring players (b) are truncated for hours 1–4. As is clear, the mean performance shown in (a) does not represent the progress of any individual player (b). From Destefano and Gray (2016).

more notable for its plateaus, dips, and leaps (Gray and Lindstedt 2017) than for smooth and steady improvement with practice.

Following Thorndike (1913), we distinguish between “spurious limits... which could be surpassed” and limits due to “the mechanism for the function itself” (Gray 2017). We call the former plateaus and the latter asymptotes. Hence, a new method for completing an old task results in the overcoming of a plateau, whereas an improved tool or a general enhancement of some sort to a brain area raises an asymptote.

The plateau versus asymptote dichotomy is often clear in hindsight when we can show that individuals performing at different skill levels are doing different things. A paradigmatic example is the distinction in high jumping between the Scissors and Straddle versus the Fosbury Flop techniques (see Figure 10.2). In the 1960s, performance in high jumping appeared to be topping out (in our terminology, it was thought to be asymptoting) as only incremental increases (measured in millimeters) in world records were being realized due, primarily, to a larger participant pool and better physical training. Then Dick Fosbury came along in 1968, “flopped” and smashed world records. This made it clear, in hindsight, that prior high jump performance had plateaued due to the method being used, not asymptoted due to an inherent limit in how high humans can jump.

There are three types of activity capable of moving human performance off a plateau: (a) method invention, (b) method development, and (c) practice (Gray and Lindstedt 2017). We argue that method invention and method development are often (but not necessarily) signaled by dips in individual performance, and that the implementation of a successful new method may be signaled by a performance leap that takes behavior well beyond the incremental improvements available through regular practice.



**Figure 10.2** Techniques in high jumping: (a) scissors and straddle and (b) Fosbury flop. Figure used with permission from Carlos Lopez.

## Techniques: Changepoint Analysis

With the plateaus, dips, and leaps (PDL) framework guiding our work, we have attempted to develop tools to help automate the identification of change-episodes; that is, periods in which the learner discovers or invents new methods in individual performance (Destefano and Gray 2016; Gray and Destefano 2016). Although our current techniques are either not sufficiently intuitive or not sufficiently automated, we can provide an example of what we are trying to do.

The essence for our use of changepoint analysis lies in comparing multiple performance factors within the same individual at the same moment in time. This requires detailed data collection with timestamping. Figure 10.3 plots three factors (two features and one score)<sup>1</sup> for one *Space Fortress* player across each of the 248 games that he played.

Figure 10.3 uses the *intuitive changepoint analysis method* (Gray and Destefano 2016) in which a slope is computed for each factor (feature or measure) of interest. For this figure, we then computed the running slope across each of the five games (i.e., games 1–5, 2–6, ..., 244–248) of *Space Fortress* for that factor.

The horizontal line in each of the three plots is the normalized slope across all 248 games for that factor and that player. It is always plotted at zero. The other lines plot the running slope for each 5 games as deviations from the overall running slope. Hence, upward sloping lines represent an increase in a factor whereas downward sloping lines represent a decrease. In general,

- when all three factors move down at the same time, the player is probably asleep or distracted,
- when all three follow each other up and down, it is hard to conclude anything, but
- when some move up at the same time that others move down, that is interesting.

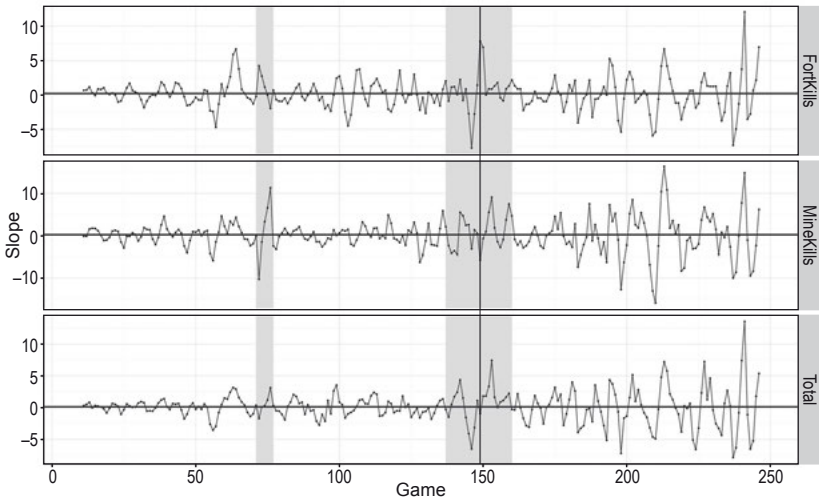
Hence, in Figure 10.3 the two gray bands were added by the analyst to highlight periods of interest; namely, periods in which some of these three factors were moving up while others were moving down.

The leftmost gray band (games 71–77) highlights periods of discrepancy between dips and leaps in Fortress Kills and those in Mine Kills. During this period the player discovers the following:

- If you kill the Fortress fast enough (the leap in FortKills between game 71–72), mines will never appear.

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<sup>1</sup> For *Space Fortress*, there are four scores that the player sees as s/he plays each game. We also collect data on approximately 30 features of game play.



**Figure 10.3** A plot of one player’s data based on two features—number of Fortress Kills (FortKills) and number of Mine Kills (MineKills)—and one score (TOTAL). See text for detailed discussion (Gray and Destefano 2016).

- By preventing the mines from appearing, your mine kills dip drastically (MineKills between games 71–72) as do the total points earned (TOTAL at game 72).
- A player thus invents, implements, tests, but ultimately rejects this strategy.

Games 137–160 are also highlighted (the vertical black line through the middle of this period is merely a visual aid for the reader). During this period, our player discovers and implements a strategy that was new to us:

1. Shoot the Fortress as quickly as possible to increase its vulnerability to “9” (without shooting it so quickly that its vulnerability resets).
2. Wait for the mine to appear.
3. Manage the mine as a “normal” mine. (*Space Fortress* has two different types of mines which need to be killed in different ways.)
4. Killing the mine gives you points and also increments Fortress vulnerability by “1” making it eligible to be killed.
5. Finally, double-shoot the Fortress as quickly as possible.

Incrementing vulnerability this way saves you the cost of “one” shot while giving you points for destroying mines.

As can be seen in this gray-banded area, across this period of thirteen *Space Fortress* games (each dot is a separate five-minute game) the total score per game fluctuates wildly. As the score stops decreasing and begins to increase (game 146), so does the number of Fortress Kills. At game 149, the number of

Fortress Kills peaks whereas the number of Mine Kills plummets and the total score returns to its average. This is a true invention. Although we programmed this version of *Space Fortress*, we were not aware that what this player invented in this sequence of games was even possible. Indeed, while several of our players discovered the strategy used in the leftmost gray band (see Figure 10.3), very few discovered this one.

In summary, applying changepoint analysis to these data supports our interpretation of dips and leaps as sometimes signaling periods of discovery, invention, and change. There is no way for knowledge compilation or other known practice-based cognitive processes to account for these discoveries.

### Applying Machine Learning Insights to *Tetris*

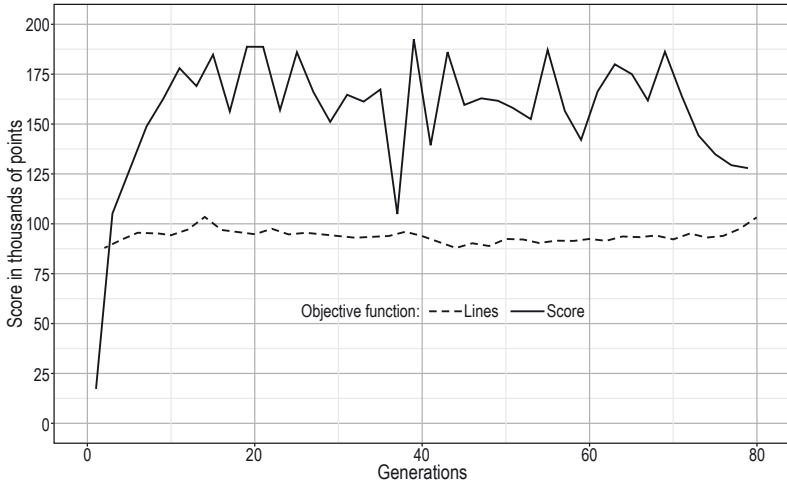
A related line of research compares similarities and differences between performance by humans and machine learning models (Sibert et al. 2017). The most recent work in this thread compares the machine learner “tortoise” with the human “hare” (Sibert and Gray 2017).

### Reinforcement Learning Modeling for Minds and Machines

To handle the pattern-matching component of placing a new *Tetris* piece (or zoid) in the pile of existing pieces, we turned to the feature learning method of cross-entropy reinforcement learning (see Sibert et al. 2017). Janssen and Gray (2012) discuss three parameters of reinforcement learning which could be modified to better match human learning and practice: when, what, and how much to reward. The “what” component was interesting to us because all *Tetris* machine modeling research we could find reinforced the “number of lines cleared.” These models played a lot of episodes (often over 300,000) and cleared a lot of lines (often over 100,000). At that time the best player we had in our lab played for 506 episodes (one zoid per episode) and cleared close to 200 lines. We wondered if playing for lines versus playing for score would produce different weights in our feature sets and affect performance. Both of these things happened. As Sibert et al. (2017) show, the different feature rates were learned for the two objective function conditions and, when judged by total score per game, the lines model rapidly plateaued at around 100,000 points whereas the score model peaks around 200,000 (see Figure 10.4).

Figure 10.4 shows that the lines controller (which is the one always used by the machine learning community) produces a flat function across its many generations, whereas the score controller shows plateaus, dips, and leaps. At first this finding seems like an interesting mystery. On further thought, it seems completely understandable and provides a bit of an “ah-ha” moment.





**Figure 10.4** Learning curve of models. In each game and generation, the total number of zoids available is 506. At the end of each generation, before the next set of 100 controllers is generated, the new starting controller played 30 test games (for details, see Sibert et al. 2017). The mean performance for these 30 games, for each of the 80 generations of training trials, is plotted here. Adapted from Sibert et al. (2017, fig. 3).

The lines model is playing to clear the maximum number of lines it can and it does this extremely well. With 506 zoids, the maximum possible is 202 lines cleared. Most of these clears are 1-line clears—not 2-, 3-, or 4-lines. Hence, when the y-axis plots score (as we do in Figure 10.4), this model’s score is about as high as it can be by clearing one line at a time.

In contrast, the score model is clearing more 2-, 3-, and 4-lines. As the score function rewards multiple line clears (e.g., clearing 4-lines at once yields 7.5 times as many points as clearing 1-line, four times), the score model learns to maximize points by maximizing the number of simultaneous lines cleared. However, the zagging line for score in Figure 10.4 shows that this is a risky maneuver. Doing multiple line clears requires allowing the average board height to become higher than for 1-line clears. This is a dangerous trade-off because when the board becomes too high and the stack of zoids reaches the top of the screen, the game ends.

### A Necessary Digression: *Tetris* Technicalities

There are several key differences between machine and human play of *Tetris*. As the level increases, the time it takes a zoid to drop 20 lines keeps decreasing. At level zero, an unhampered zoid would fall 20 lines in 16 sec (to the bottom of the board). At level nine it drops the same distance in 2 sec. By level 16, the drop takes 1 sec. At level 19, the fall takes 0.66 sec. For human play,

the drop rate tops out at 0.33 sec to fall those same 20 lines at level 29. Clearly, such rates of fall present a significant challenge to human perception, action, and decision making. To motivate humans to play faster and faster (and some of the champions at the annual Classic Tetris World Championships do play beyond level 29), the number of points awarded for clearing lines “escalates” as a function of drop rate.

In contrast to humans, the machine models (MM) evaluate the goodness of all possible placements in a blink of the eye and “move” the piece to that location instantly. There is no difference for them between play at level zero, level 30, or level 12,000. If we began rewarding the model at level zero rates (the “base” score) and escalated the scoring system beyond level 30 (the highest level reached by humans) all the way to level 12,582 (the highest level reached by our models), the model’s escalated score would be 34,847,635,540 points.

With such escalated scores, it becomes misleading to compare MMs at high levels of play to each other and certainly to humans. Hence, we have adopted the convention of presenting base scoring and escalated scoring. When we are discussing the long games played at levels only achieved by the MMs, we always use base scoring, which rewards *Tetris* play at all levels the same as for level zero. However, when we are within human levels of play, we report both escalated and base scores.

### The Tortoise and the Hare

The Sibert et al. (2017) study left us in a bit of a quandary, if only because the entire corpus of machine learning research on *Tetris* uses lines as their objective function. In their defense, these machine learning studies focused on developing methods for feature search, not on model behavior and, as discussed above, the models do not play under time pressure. From that perspective, we realized that by capping the number of zoids at 506, Sibert et al. (2017) artificially simulated a type of time pressure.

To investigate this issue more thoroughly, we abandoned cross-entropy reinforcement learning and took up Mind Modeling or, to be more precise, MindModeling.org (Glendenning et al. 2016; Gluck and Harris 2008). In this work, Sibert and Gray (2017) turned to a grid search of the feature space to test 3,543,122 models that each played one game. The models played in one of two conditions: tortoise or hare. In the tortoise condition, each of the 1,771,561 models played until it lost. In the hare condition, each of the 1,771,561 models played for a maximum of 506 zoids.

As shown in Table 10.1, the best tortoise/long model (row 1), which was allowed to play to its limits, scored 5,527,820 (base) points. The highest performing model in the best hare/short game condition (row 4) scored 240,900 (escalated) points, clearing 199 lines using 506 pieces. (The maximum number of lines possible to clear with 506 pieces appears to be 202).

**Table 10.1** Model scores and lines cleared.

Model	Length	Points	Scoring	Lines
Best tortoise	Long	5,527,820	Base	125,829
Best hare	Long	68,440	Base	2243
Best tortoise	Short	92,700 8720	Escalated base	202
Best hare	Short	240,900 18,900	Escalated base	199

We then allowed the best hare model to play a long game (Table 10.1, row 2), and the best tortoise model to play a short game of maximum of 506 zoids (row 3). The best tortoise model did poorly in the short condition with 92,700 (escalated) points, far below the 240,000 (escalated) points of the best hare model in the short length condition. Similarly, under long length conditions the best hare model performed well above average (68,400 base points), but scored nowhere close to the best performing tortoise model (5,527,820 base points).

### Model Behavior

The above comparisons are interesting; however, as we are focused on human behavior, we are not merely interested in the models' various scores (i.e., the "points" and "lines" columns in Table 10.1) but in their behavior. Did the differently trained models show different behaviors from each other and/or in their transfer conditions?

For this comparison, we looked at key behaviors known to separate human *Tetris* experts from novices; namely, the proportion of 1-, 2-, 3-, and 4-lines cleared. As Table 10.2 shows, the tortoise models had proportionally more 1-line clears than the hare models, but the hare ones had more 2-, 3-, and 4-lines than the tortoise ones. More interesting, the tortoise models made almost no 3- or 4-line clears (all were less than 1% of the total), whereas the hare

**Table 10.2** Model behavior: differences in the percentage of types of line clears.

Line Clear Type	Best Tortoise	Best Hare
1-Line	85.16	70.37
2-Lines	14.03	18.52
3-Lines	0.78	4.44
4-Lines	0.03	6.67

models ranged from 4.4% to 6.7%. The hare pattern of more 4- than 3-line clears shadows the pattern of our best human players.

## Summary and Conclusions

These models are not replicas of human decision making, but they provide insight into how humans make complex, rapid decisions. The Sibert et al. (2017) work showed that models trained to optimize the objective function of points performed differently than those trained to optimize lines cleared. Not only did they find that the points-trained model achieved a higher score in fewer lines than the lines model, but it better predicted performance differences between expert and novice human players. The lines model essentially did not distinguish between human experts and novices. As such, these strong differences in optimal strategies are issues which must be considered when humans partner with robots, such as is intended to be the case in the canonical uses for future ITL. To make this connection very clear, an implication of this research is that the details of the content taught to the ITL agent matter and should likely change depending on the circumstances, regardless of whether that agent is human or machine. Rather than rewarding performers for number of items completed, the reward needs to be framed in terms of number completed per unit of time.

We characterized the points-trained models as riskier than the lines-trained models because the only way to gain more points with a limited number of pieces is to do more 3- and 4-line clears. These require building higher piles than do the lines models. This, however, is a riskier strategy, and we interpret the dips and leaps in Figure 10.4 as showing that risk.

The MindModeling models support these conjectures. The MindModeling models were not reinforcement learning models; hence, there was no objective function. Using “total points” as our sole criterion, we simply selected the model that scored the most points in 506 episodes and the one that scored the most points when given unlimited play. Although the best hare model upped its score 12-fold when allowed to play long, it was nowhere near the level of the best tortoise model. Even more surprising, the best tortoise model, the one that scored more than 5 billion points, delivered a pathetic showing when it went short, a mere 92,700 (escalated) points!

It is worth noting that the tortoise-trained model completely brackets the hare-trained one. The tortoise/long scores 80 times as many (base) points as the hare/long, while the tortoise/short scores only 38% of the (escalated) points as does the hare/short (46% of the base points). These comparisons drive home the oft-missed point that “time” itself is part of Simon’s gelatin mold and to a large degree the methods we choose are proportional to our time horizons.

## Finding the “I” in Team

Our first two paradigms, *Tetris* and *Space Fortress*, focus on individual performance and individual interactions in dynamic task environments. Our third paradigm is the game *League of Legends* (LoL), which is the most popular game in the wildly popular genre of multiplayer online battle area games (MOBAs). (For further information on LoL, see <https://goo.gl/d7mcs8>.) Our research on LoL focuses on finding the “I” in team. The term “team” is not rigorously defined in psychological science; many things in which more than one person is involved are often casually referred to as “team tasks” and the group of people who are involved in those tasks are considered “teams.” We will not provide a taxonomy of teams but will provide examples of the characteristics we are studying.

In common with *Tetris* and *Space Fortress*, LoL takes place in a dynamic task environment. Also like *Tetris* and *Space Fortress*, for LoL, doing nothing requires a decision to do nothing. In *Tetris* the environment acts on the human agent via the zoid that appears and the frequency and recency with which each of the seven differently shaped zoids occur (Sibert and Gray 2018). As players demonstrate competence by completing levels, the environment literally speeds up so that the time required for a zoid to drop 20 rows began as 16 sec at level zero, sped up to 1 sec by level 16, and topped out at 0.33 sec at level 29 (few players ever get above level 16).

Compared to *Tetris*, in *Space Fortress* the environment is more overtly hostile to the player and vice versa. Mines spawn randomly and are attracted to the player’s ship which they try to ram, thereby blowing up the player’s ship and themselves. The “Space Fortress,” after which the game is named, is less suicidal than the mines, as it primarily defends itself from player attacks by trying to shoot and destroy the player’s ship.

In contrast to these games, the lure of LoL is that the environment is not just dynamic and not just hostile; instead, it is intelligently hostile and cleverly dynamic. Although there is more to the LoL environment than just the overtly hostile five people on the opposing team, this is the main feature. They are trying to kill you. Many, if not most, of the players have a lot of experience playing together as a team (e.g., teams that have played together hundreds of times are not uncommon) and with attacking opposing teams with the goal of defeating them.

Of course, there are two major ways of describing the differences between our first two paradigms and LoL. The first, taken above, is to discuss the dynamism and hostility of the task environment. The second is that LoL is a team event; this is the key difference between LoL and the first two games and is, for us, the most interesting feature of LoL. It also is the feature that ties this game even more closely to IITL, because team members are able to learn interactively

from each other during game play. We discuss this feature further after a brief introduction to the game.

### **What Is *League of Legends*?**

In LoL, one team (comprised of 3 or 5 players) battles another team of equal size in matches which last about 30 minutes each. In 2012, one billion hours of LoL were played worldwide each month (Kenreck 2012).<sup>2</sup> With LoL as our paradigm, we have adopted big data (Goldstone and Lupyan 2016; Griffiths 2015) approaches to harvest play data from the web. To date we have collected 1.9 million records from 539 thousand matches. Figure 10.5 shows the “gods’ eye view” of LoL. In addition to that view, players see a third-person view of their avatar, the avatars of nearby players, and close-up views of the surrounding terrain.

LoL contains elements that are attractive for empirical studies of team performance:

- It is a team-based game with high demands for coordinated action across team members.
- It is highly instrumented, with detailed records kept on many aspects of performance.
- Its view of performance is multifaceted, with many explicit measures both at process and outcome levels.
- It enables various measures of team composition to be extracted or derived from match records, such as the working history of team members.

### **The Role Structure of LoL Teams**

Without providing a tutorial of LoL play, we stress that like other invasion games,<sup>3</sup> a player’s role in LoL is largely determined by the position played (Williams et al. 2011). For our purposes, position refers to the combination of the lane a player occupied and the role they fulfilled. LoL players may occupy the (a) top, (b) middle, or (c) bottom lane or (d) the jungle (i.e., the territories in between the lanes) (see Figure 10.5). There are five roles a player can fill: none, duo, duo support, duo carry, and solo. Different roles are available for the different lanes, resulting in sixteen different positions that a LoL player could play.

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<sup>2</sup> For readers who are unfamiliar with LoL, we advise viewing the five-minute overview on YouTube before proceeding: <https://goo.gl/d7mcs8> (accessed Feb. 10, 2019).

<sup>3</sup> See “Teaching Games for Understanding” at <http://tgfu.wikifoundry.com/page/Helena+Baert> and “What Are Invasion Games” at [https://thephysicaleducator.com/game\\_category/invasion/](https://thephysicaleducator.com/game_category/invasion/) (accessed Jan. 31, 2019).



**Figure 10.5** Screenshot of a battlefield map for the multiplayer online battle arena game, *League of Legends*. The river flowing from the upper left to the lower right separates the “home” territory of one team from the other. Territories can only be crossed via one of the three lanes (top, middle, and bottom marked here by blue and red arrows). Each team begins in one of the large quarter circles shown in the lower left (blue team) or upper right (red team). These bases include the all-important “nexus” (the blue or red area closest to the lower left and upper right corners). The darker green spaces between the lines are less traversable terrain referred to as the “jungle.”

### Research Issues in Team Performance of Dynamic, Interactive Teams

“Team” is a loose concept that can be applied to many groupings of individuals. For instance, a shift of telephone directory assistant operators could be called a “team,” where the judgment of “team goodness” per shift is simply the sum of the number of calls handled during that shift. However, we would not consider this team to be either “dynamic” or “interactive.” For our purposes, examples of dynamic, interactive teams include (but are not limited to) (a) emergency response teams, (b) combat teams, and (c) sports teams for invasion games. That is, the essence of interaction for our definition of a dynamic, interactive team includes interactions among team members which directly contribute to team outcomes.

In talking about team performance, whether the team is composed of humans, robots, or humans and robots (any combination of agent types in the broader ITL framework), we can easily talk about performance at two levels:

- The team: Was it successful? Did it accomplish its mission?
- The individual team member: How well did she, he, or it do? How does the member's performance compare to that of members in other teams or in its own team?

For dynamic teams (including both traditional sports teams and e-sport teams), team outcome can be very simply defined by whether the team won or lost. However, three types of team issues must be considered:

- Individual (Figure 10.6a): Does the team outcome reflect the simple sum of each player's individual competence in carrying out her/his role independent of the other players?
- Teaminess (Figure 10.6b): Is each member of the team doing essentially the same task but to varying degrees? In this model, there are no differences in type of expertise among team members, though there might be differences in degree of expertise.
- Teaminess + Individual (Figure 10.6c): Is there a component of shared expertise but also a component of individual expertise?

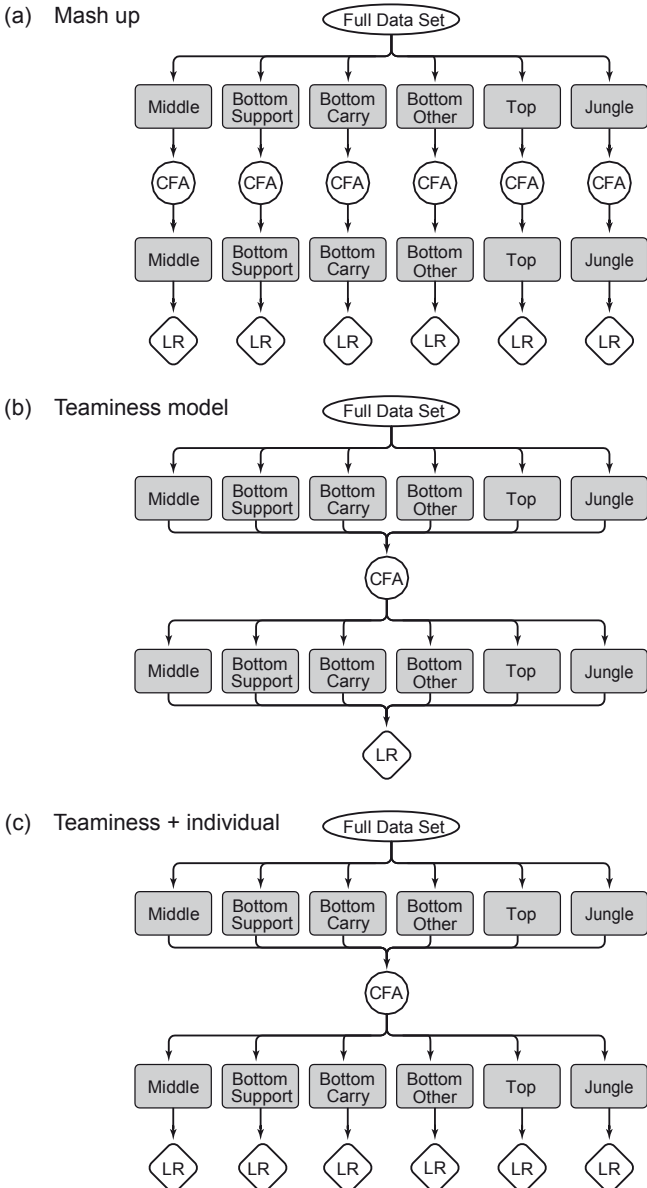
An important conundrum for these types of teams is that sometimes a team member's role does not seem to be directly connected to team outcomes. For example, in basketball it often seems as if one or two of the five players are making all of the shots and scoring all of the points. What are the other three doing? And how can we measure how well they are doing it?

### Individual Contributions to Team Tasks

The success of our work on *Space Fortress* and *Tetris* has driven home to us how important data on player skill at shifting and focusing visual attention is to understanding differences in expertise among players. Indeed, the more we study and learn from individual experts, the more we believe that an important component of "team member" expertise and/or of "expert teams" is how individual team members divide and overlap their visual attention. Perhaps somewhat counterintuitively, it may be an individual's expertise at attending to other team members that creates an expert team.

Our strongest conclusion, so far, is a methodological one; stated metaphorically, *if you want to understand how a clock works, you have to understand the clockwork*. You have to understand what each part is doing, what parts it interacts with, and the nature of those interactions. We believe we will not understand the "I" in team until we understand the expertise of individual team members. Interestingly, the second edition of the *Cambridge Handbook of Expertise and Expert Performance* (Ericsson et al. 2018) contains 42 chapters and 969 pages, but only one chapter devoted to team expertise. Although that chapter is written by expert team researchers, we have difficulties relating their discussion to the measures and factors that we have found in our





**Figure 10.6** Three possible models of team and individual performance in dynamic, interactive team tasks. (a) Mash up: six independent models where each role/position model includes a teaminess and an individual component but to unknown degrees. (b) Teaminess model: one model for the entire team. Each individual is viewed as having more or less of that one model. (c) Teaminess + individual: all data is used to find the best fit for each player position. This model captures both the teaminess component and the individual component.

teams. Perhaps the way forward for understanding team expertise in dynamic, interactive task environments is to follow the “joint action” community (e.g., Knoblich et al. 2011; Sebanz and Knoblich 2009) and focus on the second-by-second interactions among dyads, triads, and tetrads. In this effort, having one or more ITL team members, whose behavior could be programmed as well as learned, might make ITL (as represented by many of the other chapters in this volume) a core topic in team research and, at the same time, make team research the overarching perspective on ITL.

### **Paradigms for Discovering the Essence of Interaction: Action Games**

Our discussion of the essence of interaction started with the plateaus, dips, and leaps framework, which focuses on individual performance over time. The discovery of inventions made by one player after about 9 and almost 20 hr of play highlights the point that the slow-but-steady mechanisms of incremental learning simply cannot account for the dips and leaps seen in skill acquisition.

We then jumped to our machine learning data and used these models to explore the “optimal possible performance” once a certain objective function was adopted. We used the MindModeling system to access large-scale computational resources and perform a grid search across a parameter space covered by 1,771,561 models. That work dramatically demonstrates that “slow and steady” wins the race, but only when the race is long. When it is short, as it is for humans, the best hare model wallops the best tortoise model.

Jumping back to humans, one conclusion from our current work on “finding the ‘I’ in team” is that solving the “team problem” requires solving the problem of individual expertise. In addition, a methodological revolution is needed in both team studies and studies of ITL, and that revolution might be fueled by the methodological techniques and insights of the joint action community. Finally, if we are talking about intelligent, autonomous, robots and software agents, then there may be few inherent differences in the ways we study human-only teams versus mixed human–machine teams.

### **Paths Forward?**

The central question addressed at this Forum concerned the acquisition of new tasks through natural interaction. Here, we have provided examples of human behavior in task environments that are interactive, dynamic, and require sequential decision making. For such task environments, action games provide a right-sized challenge, and we have provided our answer as to the sorts of methodologies and studies that should be done.

A perennial problem in the psychological sciences is collecting the massive amounts of detailed data required to draw strong inferences regarding the

research question of interest. Indeed, a conclusion that we and others draw from the current “crisis” in data analysis (Baker 2016) is that most studies have too few subjects and too few samples of data. If, as a field, we are truly interested in studying human interactive behavior, we must collect detailed data from many subjects. If we are interested in how interactive skill is acquired over time, then we need to run longitudinal studies, sampling expertise from a very large number of performers across a wide range of skilled performance, or both.

This problem with longitudinal or sampling studies of expertise represents the standoff which the human factors community has been battling for decades. We advocate confronting this standoff by taking advantage of the availability of vast numbers of people on college campuses who have acquired almost obscene levels of excellence in action games. Of course, what makes these campus activities so useful is the electronic nature of the tasks and the realistic prospect for researchers to collect detailed data with millisecond precision. Indeed, our current conclusion is that the study of ITL needs to follow the “joint action” (e.g., Knoblich et al. 2011; Sebanz and Knoblich 2009) path of detailed empirical studies (e.g., Vesper et al. 2009) rather than the traditional “team studies” path of eschewing the direct observation of millisecond level interactions among team members.

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