Building a Worthy Opponent

Simulating Human Play for the Development of Expertise

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Abstract

This paper considers what is required of a sufficiently powerful, and realistically human, game-playing program. It summarizes relevant human performance data, and distinguishes fundamental properties of human and of expert human play. Learning, planning, and visual perception are emphasized, as well as communication. The resultant programs should offer competition, instruction, and collegial discussion.

Introduction

There are several reasons one might want to construct a human-like agent to play board games. A person might enjoy competition against a strong (human-like) player. A person might learn to play better with a program that could analyze and discuss contests. Finally, a person might enjoy interaction with another aficionado. The concern here is not believability, but skill and communication.

The construction of a good simulated agent (a *worthy opponent*) for game playing, however, is a challenging task. Many popular board games have time limits, so that contestants must perform under time pressure. Moreover, one player often competes against many others, so that the agent's environment is dynamic. Although one might expect that human experts would be the obvious models for a worthy opponent, at the moment expert machine players and expert human players are very different.

The expert machine game player is engineered. Such a program typically relies on an extensive *opening book* (moves early in contests), high-speed search through thousands or millions of possibilities, and perhaps a vast lookup table of *endgame* play (late contest states and the correct moves there) (Schaeffer 1997). A machine player may also rely on specialized hardware, as Deep Blue did (Campbell 1999). If the program learns portions of its evaluation function or its knowledge base, that learning is usually done offline, in thousands or millions of contests (Buro 1999; Campbell 1999).

The expert human game player, in contrast, is a marvel of economy. In the course of a year, a chess grandmaster, for example, plays perhaps a dozen different openings in perhaps a thousand contests (Holding 1985). The grandmaster considers only four or five possible next moves, and rarely searches deeper than nine ply, typically with an alternative or two at each step. The human expert knows the value of certain endgame positions with a schema for executing them, but does not often reach that far in search during play. And the human expert learns that skill on-line.

Throughout this paper, *game* denotes a set of rules, playing pieces, and a board, while *contest* distinguishes a single experience playing a game. A *state* is a situation in a game, described completely by the location of the playing pieces on the board and whose turn it is to move. For example, tic-tac-toe is a game at which two people might play a contest, beginning with a state that is an empty board with X to move. The *game tree* for a game is the space of all its possible states, connected by the moves that lead from one state to another.

This paper describes some properties of human game players, and addresses the sources of their power. It goes on to consider what features machines need to simulate human play and yet provide challenging competition. Empirical results with one program are included.

Human Game Players

Consider first the behavior of ordinary game players. In one study, 8 college students were recruited to play three two-person, perfect information, finite-board games against a computer (Ratterman and Epstein 1995). As competition, three opponent programs were constructed; each was a *perfect player*, that it is, each was designed to make the best possible move in any state and, if there was more than one such move, to select a top-quality move at random. The games in this experiment were tic-tac-toe, lose tic-tac-toe, and achi; they are described in Figure 1. Each of them is a *draw game*, that is, with perfect play on both sides, every contest would result in a draw.

The subjects were asked to "think out loud" while they played, and their verbal protocols were tape recorded. Each person encountered the three games in a randomized order. A game was played until the subject drew 7 consecutive contests or had played 25 contests. Based on their performance, four of these subjects were rated as skilled game players and the other four as unskilled game players, using contrastive analysis (Chi, Bassok, Lewis, Reimann, and Glaser 1989).

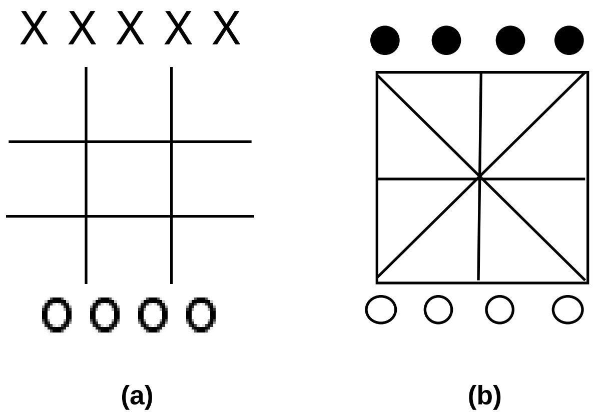

Figure 1: The game boards for (a) tic-tac-toe and lose tic-tac-toe, and (b) achi. *Tic-tac-toe* is the well-known game, where a win is three pieces (either X's or O's) in a row either vertically, horizontally, or diagonally. *Lose tic-tac-toe* is a variant of tic-tac-toe played on the same board, in which three pieces in a row lose the game. *Achi* is played between black and white. Contestants at achi begin with 4 markers and alternately place them on the board at the intersection of two or more lines. There are nine such positions, corresponding to the nine positions on the tic-tac-toe grid. Once all eight markers have been placed on the board, a turn at achi consists of moving one's own piece to the single empty position. A win at achi is three pieces in a row. Play ends in a draw when the same state is cycled through an agreed upon number of times (3 here).

After playing all three games, the subjects were given a list of 17 *commonsense principles* (generally applicable rationales for move selection) that might be brought to bear on play, and asked to rate their effectiveness, how often they had used them, and in what order, for each of the games. These principles are listed in Table 1. Answers were compared with the transcribed protocols. The commonsense principles frequently appeared in the protocols and were also confirmed by the subjects in their written answers.

The more skilled game players in this experiment verbalized most of the Table 1 commonsense principles in their protocols, and used them more often than the less skilled players. The skilled players also valued the commonsense principles more highly in their decision making than the unskilled players. More skilled players also used two of the principles, Defense and Patsy, less often than less skilled players. (The prevalence of a variety of competing, possibly inconsistent, principles supporting expertise is not uncommon; it has been detected in other domains as well, e.g., (Biswas, Goldman, Fisher, Bhuva, and Glewwe 1995), (Crowley and Siegler 1993).)

Expert Human Game Players

Expert human game players have been the focus of study for more than 100 years (e.g., (Binet 1894)). Psychologists have found in them no evidence of exceptional concentration, enormous memory, high IQ, extensive forward search into the game tree, statistical measures of typicality, or concrete visual images (Binet 1894; Charness 1981; Djakow, Petrowski, and Rudik 1927; Holding 1985). Nonetheless, human experts play faster and better than novices.

Skilled human game players have better memories, but only for meaningful patterns, that is, ones that could arise during play (Chase and Simon 1973). Evidence suggests that such a memory maybe organized around higher-level concepts or around prototypes (Eisenstadt and Kareev

Table 1: Commonsense principles and their definitions as described to the subjects.

Principle	Definition
Blinders	Select a move to further a simple plan, with no regard for your opponent's plans.
Defense	Select a move to defend against your opponent's simple plans.
Don't Lose	Do not make a move that will result in a loss.
Enough Rope	If your opponent would have a losing move on this board, avoid blocking it, i.e., leave the opponent the opportunity to "hang itself."
Fork	Chose a move giving you more than one opportunity to win, while blocking moves giving your opponent more than one opportunity to win.
Greedy	Make moves that advance more than one winning configuration.
Lookahead	"Look" two moves ahead, and based on this choose your next move.
Panic	If your opponent has a winning move on this board, block it.
Resign	If this is a certain loss, resign.
Victory	If you can find a winning move, take it.
Again	Repeat winning or drawing moves you have made.
Not Again	Do not repeat previously losing moves you have made.
Copycat	Mimic opponent's winning or drawing moves.
Leery	Avoid moves that your intuition tells you have led to a loss in the past.
Patsy	Reproduce the visual pattern made by the pieces of the winning or drawing player, and avoid the visual patterns made by the pieces of the losing player.
Start	Repeat previously successful observed opponent's opening.
Win	If you remember a certain win, make the winning move.

1975; Goldin 1978) rather than perceived patterns. A long-standing theory advocated *chunks* (unordered spatial patterns) as the foundation of chess grandmasters' skill. More recent work, however, has focused on the far more difficult game of Go, which has hundreds of pieces and a branching factor roughly 10 times that of chess.

Go masters do not appear to have such chunks (Reitman 1976). Instead, protocols and eye movement studies on expert Go players (Burmeister, Saito, Yoshikawa, and Wiles 1997) indicate that perception is interleaved with cognition, as demonstrated in timed photographs of a chess player's brain (Nichelli, Grafman, Pietrini, Alway, Carton, and Miletich 1994). The Go players, it appears, are able to narrow their perceptual focus to only a small part of the board, and actually look between the *stones* (playing pieces) rather than at them, as if considering their options. (A Go move is the placement of a stone on one of hundreds of grid intersection points.) Master Go players' searches are, on average, only 4-ply deep and no more than 3 moves wide. The patterns these players perceive are dynamic, and they readily annotate those patterns with plans.

Moreover, Go players' memories appear to be cued to sequences of visual perception (Yoshikawa, Kojima, and Shingaki 1999). Stronger players remember professional contests better than randomly played ones. Stronger players are also better able to replicate a position they have watched emerge from a sequence of plays than one that has been presented after the fact. Indeed, strong players always attempted to replicated a state as if it had emerged from competition, alternately placing a black stone and then a white stone on the board, even when the state had been generated randomly. In another trial that used auditory cues (verbal descriptions of the location of pieces, with or without some descriptive Go terminology) instead of visual cues, similarly strong players failed to recreate states from expert play. Visual perception was essential to their memories. Surprisingly, in Shogi (a chess-like game played with 40 pieces on a 9×9 board) auditory cues were as effective as visual ones.

Realistic Game-Playing

Some features of human play are by now traditional in strong game-playing programs. A good human player will remember previous significant experiences; many programs have knowledge bases to which they refer. A good human player will not need to re-expand the same portion of a game tree more than once in a contest; many programs have transposition tables that serve the same purpose. A good human player knows the importance of openings and remembers and employs a variety of them; many programs have extensive opening books. A good human player recognizes and employs endgame knowledge; many programs have similar information.

There are, however, a variety of features that describe human expertise, features that programs generally lack. A good human game player plays faster in familiar situations or when the other contestant makes a foolish move, and slower when the other contestant makes a strong move. Indeed, a good human game player constructs a model of her opponent, and makes decisions accordingly. A good human game player has a variety of rationales for her behavior, and is able to offer an explanation for her action, one that may include alternative move sequences. People use visual perception to organize their memories, and appear to have sequential patterns as well as static ones. People learn to play better as they play more, they readily annotate their play with the motivations behind their choices, and they plan. Moreover, human experts play faster when they know more, while many programs play slower. This human speed up is known as the *shift to automaticity.*

A cognitively plausible program

Hoyle is a program that has been judged cognitively plausible in both its construction and its performance (Ratterman and Epstein 1995). Hoyle is based on *FORR* (FOr the Right Reasons), an architecture for learning and problem solving (Epstein 1994a). FORR's thesis is that there are many good reasons for making a decision in a particular domain, and that a combination of those reasons should be sufficient to learn to perform expertly.

In FORR, each good reason is called an *Advisor*. Hoyle's Advisors may be thought of as good reasons for making a move. The rationales in Table 1 are actually paraphrased (and in some cases, renamed) versions of some of Hoyle's Advisors. Theoretically, an Advisor can be structured around any kind of computation, but FORR-based programs have traditionally eschewed deep search in favor of heuristic rationales.

Each Advisor is implemented as a procedure whose input is the current world state, the choices available to the decision maker, and acquired *useful knowledge*, learned data that is potentially applicable to future experience but only probably correct. An Advisor's output is a set of comments, at most one for each choice. A *comment* indicates the degree (*strength*) to which that particular Advisor supports or opposes an individual choice.

Hoyle uses a mixture of game-playing Advisors to select a move. Tier-1 Advisors take priority. For example, since the objective in game playing is to win and Victory is always correct, there should be no debate between Victory and any heuristic Advisor. The tier-1 Advisors are presequenced by the programmer and consulted in order. If any one of them can make the decision, it does so, and none of the remaining Advisors in any tier is consulted. For the most part, however, tier 1 does not comment, and the decision proceeds to the heuristic Advisors. They are consulted in parallel, and their comments combined to make a decision. Heuristic Advisors vary in their relevance from one game to the next. An Advisor for piece capture, for example, is less important in tic-tac-toe than certain other Advisors, although that may not be the case in every game. For this reason, FORR provides a weight-learning algorithm that combines the heuristic Advisors' comments .

Prior to the work reported here, all Advisors were prespecified by the programmer and potentially applicable to every problem class. Recently, however, Hoyle has begun to learn perceptually-based, game-specific Advisors (Epstein, Gelfand, and Lock 1998).

Hoyle begins as a novice at any game; it learns *useful knowledge* (probably correct and possibly reusable) information as it plays. Each kind of useful knowledge is prespecified by the programmer, with a learning time and a learning algorithm. For example, a good opening is learned by rote after a contest. Each kind of useful knowledge is expected to be relevant to every game, but the *values* for a particular useful knowledge item are not known in advance. Openings, for example, must be learned, and vary from one game to another. This is what is meant by *game-specific* useful knowledge.

In the college student experiment described above, the overlap between the way Hoyle makes decisions, and the way good human game players reasoned and believed they should reason, was quite high. Moreover, the human subjects and Hoyle favored the same principles/Advisors on the same games, and found the games difficult to learn in the same order. A cognitive psychologist judged Hoyle "a plausible model of the acquisition of expertise in humans" (Ratterman and Epstein 1995).

Formulating a Worthy Opponent

This section addresses the reasons for construction of a human-like agent to play board games: competition, education, and consultation.

The worthy opponent as competitor

For shogi and Go, programs in the style of Deep Blue have not produced even strong amateur play. The creation of large, useful endgame databases is unlikely, because there are as many or more pieces on the board in the endgames, and often a larger branching factor. Knowledge for a heuristic evaluation function is also problematic. In shogi, unlike chess, there is no consensus even on the relative strength of the individual pieces (Beal and Smith 1998). In Go, unlike chess, the rules distinguish no stone from any other of the same color; a stone's significance is determined by the state. There are, moreover, thousands of possible Go features whose interactions are not well understood. To excel at games like shogi and Go, programs, I believe, will require a cognitive orientation.

Based on the results discussed earlier, Go masters depend upon sequences of actions. Some work has begun in that area. Lock (Lock, in preparation) has extended Hoyle to learn sequences of actions in a variety of ways. In small games (e.g., lose tic-tac-toe) she has demonstrated a human-like shift to automaticity. In slightly larger ones (e.g., five men's morris in Figure 2) she has also demonstrated performance enhancement. Shih, meanwhile, has developed a case-based approach to sequence learning (Shih 2000). Bridge is a card game whose imperfect information makes deep search intractable. Shih has shown that it is possible to learn variable-length sequences of state de-

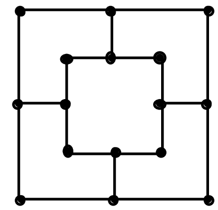

Figure 2: The game board for five men's morris. Play is between two contestants, black and white, each with five playing pieces. In the placing stage contestants alternate placing their pieces on any empty *location* (the 16 intersections marked on the board). In the sliding stage a move slides an owned piece along a predrawn line on the board from one location to an immediately adjacent empty location. Three pieces of the same color on a predrawn line form a *mill.* When a move forms a mill, the mover captures any piece belonging to the other contestant, a piece not currently in a mill if there are any. Play terminates with a win for the non-mover whenever the mover is reduced to two pieces or cannot slide. Otherwise, a draw is declared when play cycles three times through the same state or the contest exceeds some fixed length (here, 80 moves). This game is non-trivial: contests between strong players average 65 moves in a search space of about 7 million states.

scriptions for three-no-trump contracts, and then use them to play out a bridge hand surprisingly well.

Human Go masters also rely on visual perception to organize their memories and focus their attention. Given their current weak level of play, it seems clear that Go programs should move in this direction. Although patterns are noticed and exploited by people, purely pattern-based play is not successful, even on the three games of Figure 1 (Painter 1993). Nonetheless, Go texts associate particular patterns on the board with names (e.g., ladder), and have standard responses to them. When Hoyle learns to observe simple patterns and apply the successful ones, its performance on small games such as lose tic-tac-toe is substantially enhanced (Epstein, Gelfand, and Lock 1998). The patterns Hoyle uses are derived from templates (L's, V's, straight lines, squares, and diagonals of squares) prespecified by the programmer, but Hoyle sizes and locates them on the game board, and then learns to associate contest outcomes with those patterns. Hoyle also constructs and uses new, pattern-based Advisors that are particularly salient generalizations over patterns.

Nonetheless, for slightly more complex games, simple patterns are unlikely to address the shapes crucial to expertise. The controlled generation and learning of important patterns remains an open question. A second perceptual enhancement to Hoyle, however, appears more promising. The program now has a language with which to describe how territory on the board is held by winning, drawing, and losing contestants. As it plays, Hoyle learns how to describe territorial control, and then uses those descriptions in games such as five men's morris to make better moves (Epstein, submitted for publication.). Hoyle also constructs and tests new, territorially-oriented Advisors for particularly salient expressions. Since Go is a game about territorial control, such an approach could prove valuable.

Finally, the development of expert players for games that people do not understand well must to some extent rely on machine learning. If we cannot infuse a system with enough of our own knowledge, we must ask it to produce that knowledge itself. This approach has been successful deductively in checkers (Schaeffer 1997) and inductively in Othello, backgammon, and Scrabble (Buro 1998; Sheppard 1999; Tesauro 1995).

The worthy opponent as tutor or colleague

For both instruction and consultation, a worthy opponent needs some ability to converse with the other contestant about the behavior in question. Initially, this might be of the form "nice move" when it is one the program's evaluation function would have chosen, or perhaps "that's a surprise" when it is not. Fundamental, therefore, is the notion of choice (or lack thereof when a move is forced).

Fundamental too are the devices that people use. Discourse alone will not suffice. Demonstration (playing out one or more sequences of moves) and highlighting key actions and locations diagrammatically are also essential to good communication. A worthy opponent must recall significant contests and game states, although significance is for the moment ill-defined. A worthy opponent will maintain a transposition table, and be able to refer to a possible move as one that was anticipated when an earlier choice was made. A worthy opponent will also be knowledgeable about both openings and endgame play. The former must be a focus of attention in dialogue and in instruction, including variations; the latter must be associated with actions that achieve or thwart a desired outcome. Whether or not the program requires visual perception to play well, it must be able to cast descriptions in that perspective when good communication requires it.

A worthy opponent also needs some machine-accessible representation of the rules of the particular game, both to prevent illegal moves and to focus its attention. The notions of defensive and offensive play are fundamental here; the notions of risk, and of protecting and attacking pieces or territory follow close behind. Given the rules, a program can identify moves that are likely to support aggressive behavior (e.g., piece capture or preparation for it) and also moves that are likely to put it at risk. Early work on this merits further exploration (Pell 1993). Whether or not a loss is irrevocable (can you recapture your own lost piece? balance that loss by capturing another?) is also an important component of discussion.

A worthy opponent also needs some knowledge of intentionality. In a game, the goal is to win, but there are usually subgoals (e.g., piece capture, pawn promotion) that, while not essential, may support progress toward that goal. Fundamental, therefore, is the notion of a sequence of actions and also of a *plan*, a sequence of actions intended to achieve a particular goal. A worthy opponent can expect that a human will perceive and act sequentially; it therefore must be able to plan itself, and to teach a pupil to plan. This requires the ability to extract purposeful sequences of actions and reapply them appropriately, as both Lock and Shih have done. More difficult is the formulation of a plan directed to a particular subgoal, and the construction of a plan for an entire contest from a set of subgoal plans. For example, in the play of a suit-contract bridge hand, one might decide to pull trump, establish a secondary suit, and then take high-card tricks. This is a *strategy*, an overall plan for the development of the contest. Within the strategy, there are several shorter-term plans or *tactics.* One might, for example, establish a secondary suit by playing it until the opponents are void, or by taking a finesse. Selection of individual tactics and their serialization or interweaving to form a strategy is an important open research topic.

Over-reliance on stored knowledge hampers explanations; "the transposition table said so" is simply not a satisfying rationale for a person at any skill level. Given people's propensity to play based on commonsense principles, the ones in Table 1, as well as Hoyle's learned pattern-oriented and territorially-oriented Advisors, would be a good place to begin. A worthy opponent could then merely paraphrase each Advisor to produce an explanation, such as "I made that move because it established this pattern [the program produces a diagram here] which appears to be associated with successful play, and because when I used this move in the past it was successful in this situation." Such an explanation would be enhanced by some search results of alternatives suggested by the program's evaluation function. A worthy opponent must be equipped with vocabulary that supports discussion, on which human interaction in this domain depends.

There are, finally, probably as many theories on how to teach game playing as there are human players. The classic devices are examples drawn from expert performance (e.g., newspaper columns) and competition. Some work on the nature of a good trainer (Epstein 1994b) has recently been extended (Epstein, submitted for publication) and merits attention. Particularly important there are the inherent weakness of learning to play against oneself, the importance of a strong opponent, and the detection of *key nodes*, states with important lessons to impart.

In summary, expert human game players focus their attention with perception, and rely on carefully organized knowledge and efficient procedures to manipulate that knowledge. Such people learn and plan, and employ diagram-annotated discourse to communicate with each other. A machine–human pair should strive for similar expertise.

Acknowledgements

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