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Trends in
Cognitive Sciences

Spotlight

Searching for answers: expert pattern recognition and planning

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Does expertise mostly stem from pattern recognition or look-ahead search? van Opheusden *et al*. contribute to this important debate in cognitive psychology and artificial intelligence (AI) with a multi-method, multi-experiment study and a new model. Using a novel, relatively simple board game, they show that players increase depth of search when improving their skill.

A classic question in cognitive psychology and artificial intelligence (AI) concerns the respective roles of pattern recognition and search in the development of expertise. Is expert decision-making underpinned by the ability to recognize meaningful patterns that elicit possible courses of action, or by the ability to anticipate future states using greater depth of search? The classic answer in AI, exemplified by Deep Blue's match victory over world chess champion Gary Kasparov in 1997, was to use massive brute-force search. Recently, with the advent of AlphaZero, the pendulum has swung to mechanisms based on pattern recognition [1]. In cognitive psychology, the preferred mechanism has been pattern recognition [2], although, in a recent study, van Opheusden [3] and colleagues put search back to the foreground. Curiously, then, explanations in psychology have evolved in an opposite direction compared with AI.

Chess has been a key domain in this debate. Starting from the 1960s [4], proponents of pattern recognition have emphasized the role of perceptual knowledge and intuition, culminating with Chase and Simon's chunking theory [5,6]. However, several studies also found that depth of search increases with expertise [2]. This tension was resolved in part with the SEARCH model, which demonstrated how a larger number of chunks in long-term memory facilitates search [7]. Specifically, SEARCH explains how an increasing number of chunks leads to increased depth of search and decreased processing time.

van Opheusden *et al*. [3] examined increases in depth of search during the initial development of expertise in a relatively simple board game (four-in-a-row, Figure 1A). They developed a computational model and carried out eight experiments. Their model is based on best-first search, an AI heuristic-search algorithm [8] that prioritizes exploration of the most promising paths. Board positions are assessed through an evaluation function and search gives preference to the positions with higher scores, resulting in relatively small search trees. The model comprised ten parameters, including the size of the search tree and weight of the features of the evaluation function, which were optimized for each participant using a cross-validation methodology.

The model was validated through multiple experiments, which covered human versus human games, human versus computer games, evaluation tasks, two-alternative forced choices, and games played under time pressure. Most experiments used modest samples (typically 30 to 40 players), but large-scale mobile data were collected online (1 234 844 players), with data from 1000 players analyzed. Analyses focused not only on the moves chosen but also compared human eye movements and response times with their simulated counterparts. The authors also followed the development of participants' performance over five sessions. Depth of search, inferred through model parameters, increased with training sessions (from about five moves at session one to about six moves at session five).

The great strengths of these studies are the number of different methods used and the large variety of human experiments, which provide converging evidence on the role of search in decision making. Also impressive is the combination of big data collection together with fine-grained analysis of laboratory data.

These strengths come at some cost. Although the game allowed a large set of data to be collected, participants were considered 'experts' after only playing for about 5 hours. In most domains of expertise, several years of practice and study are needed. This raises the question as to whether depth of search would keep increasing with further practice. Data from chess suggest a power law, with a rapid increase at the beginning and much slower increase at high levels of skill [7]. Another limitation is that depth of search was estimated indirectly through model parameters optimized for each participant. Thus, the depth estimate is conditional on both the model and the parameters being correct. Indeed, the authors recognize that these estimates should be taken with a grain of salt, as they seem higher than depths of search observed in tasks of similar complexity. This could be investigated by asking participants to think aloud when they play games and analyzing the resulting protocols using the methods of De Groot [4]. Finally, the authors use the term 'planning' for anticipation of moves, whereas the term 'search' is more common in expertise research, with the term 'planning' reserved for a more abstract form of anticipation. An important question, then, is how planning (in the latter sense) develops with expertise.

Finally, van Opheusden and colleagues' model has many free parameters, which were estimated for each participant,

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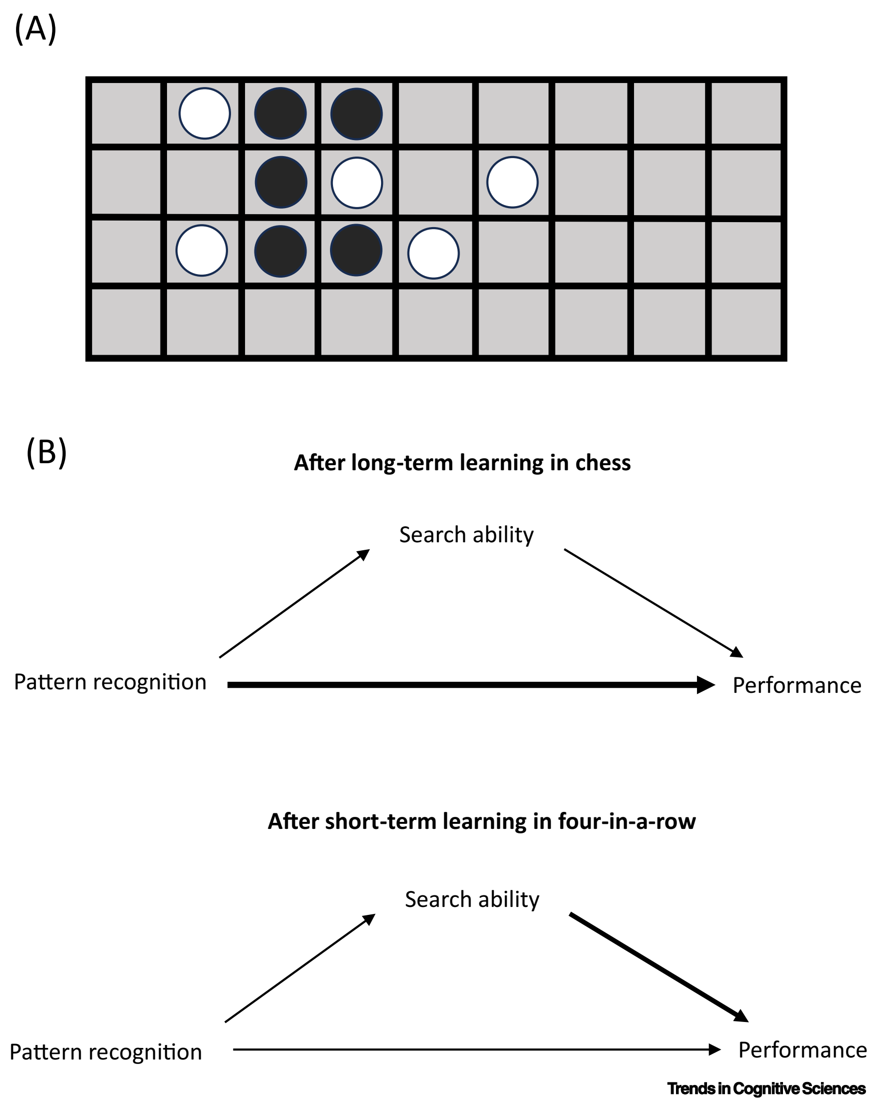

Figure 1. Four-in-a-row and the links between pattern recognition, search, and expertise. (A) Four-in-a-row, the game used in the study, can be seen both as an extension of tic-tac-toe and a variation of the Japanese game of gomoku. Players (black and white) alternate moves and place their pieces on a 4 × 9 board; the aim is to have an unbroken line of four pieces horizontally, vertically, or diagonally. The game has about 1.2×10^{16} non-terminal states, which is clearly more than most tasks used in cognitive science but far less than games such as chess (about 10^{43} states) and Go (about 10^{172} states). (B) Conceptual framework showing how pattern recognition, search, and expertise are related in theories belonging to the classic approach to expertise [5,7] and in van Opheusden *et al*. While pattern recognition dominates in classic theories (top), search dominates in van Opheusden *et al*.'s model (bottom). To understand such models, measures of pattern recognition and search should ideally be taken in the same 'subjects' (human or algorithm).

resulting in a large number of degrees of freedom. Nevertheless, the fit of model to data was sometimes modest. In addition, the model is based on best-first search, an algorithm that is normally not considered a plausible human mechanism, as it makes unreasonable requirements on working memory, including: for each state searched, computing the evaluation, which consists in identifying features and combining them linearly; keeping track of the states that have already been visited; at each iteration, selecting the state with the highest value (or lowest for the opponent); and, finally, backpropagating the evaluation of the selected terminal node.

These remarks do not diminish van Opheusden *et al*.'s contribution. By emphasizing search, they challenge expertise researchers to further scrutinize the role of search in the development of expertise, particularly in the initial stages of skill acquisition. As champions of the idea that pattern recognition underlies expertise and that 'pattern recognition makes search possible' [9] (Figure 1B), we note the view of chess world champion Magnus Carlsen (MC) (https://www.youtube.com/watch?v=USTlRy76N18):

MC: 'Most of the time, I know what to do. I don't have to figure it out. I don't have to sit there [and] calculate for 45 minutes, an hour to know what the right move [is]. Usually I can just feel it immediately...'

Interviewer (paraphrased): Why do you spend so much time looking at the board?

MC: 'I have to, you know, verify my opinion, see that I haven't missed anything. But a lot of the time it's fairly useless because I know what I'm going to do, and then I sit there for a long time and I do what I immediately wanted to do.'

Declaration of interests

No interests are declared.

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