Implicit learning of expert chess knowledge

Much of what we know about expertise comes from research into chess by de Groot in the forties and Chase and Simon in the seventies.[1,2] Two classic de Groot results demonstrated the importance of perception in expert behaviour. First, even though grandmasters found better moves than strong amateurs in a problem-solving task, there were few differences in their search behaviour. In particular, all players were selective and visited only about one hundred positions. Second, chess masters performed almost perfectly in the recall of game positions (see Figure 1) presented for a few seconds. To explain these results, Chase and Simon developed the 'chunking theory' that proposed mechanisms specifying how knowledge is implicitly acquired during practice. Expertise is seen as the acquisition of a large number of perceptual chunks (groups of features that can be used as units), that give access to relevant information (e.g., what move to play).

Over the last decade, my research has aimed to flesh out these mechanisms computationally and to test them empirically. The computational work has led to the development of CHREST (Chunk Hierarchy and REtrieval STructures), which models expertise as the growth of a discrimination net. Each node (chunk) in the net contains information about the location of pieces, as well as pointers to possible (sequences of) moves. Provision for eye-movement mechanisms enables a close interaction between perception and memory. Finally, high-level schemas are created automatically. The empirical work has investigated expert perception and problem solving using verbal protocols, eye movements, and—more recently—brain imaging. I have also manipulated several variables in recall experiments, such as time of presentation, level of position distortion, and level of position randomisation. In general, CHREST, serving as a subject 'in silico', models the memory experiments well. Here, I focus on the recall of random positions.

As documented in psychology textbooks, Chase and Simon found no skill difference in the recall of random positions (see Figure 1). However, CHREST predicts a small difference, as chunks are more likely to be recognized serendipitously in random positions with large nets than with small ones. Re-analysis of the literature, as well as the collection of new data, supported this prediction.[3]

Random positions are typically created by shuffling the piece locations of a game position. Vicente and Wang[4] noted that these positions are not really random, as they still contain information about the distribution of pieces (e.g., only one white King is allowed). They raised the question as to whether skill differences would remain if 'truly-random' positions were used, where both the location and the distribution of pieces are randomised (see Figure 1). CHREST predicts that this would be the case. An experiment with 36 players ranging from weak amateurs to grandmasters confirmed CHREST's prediction: with truly-random positions, there was a statistically reliable correlation between skill and recall performance.[5] This difference remained when variables such as age and visual memory were partialled out.

Current work with Andrew Waters further explores the role of perception in expert memory. We created positions where the pieces lie at the intersection, rather than the middle, of squares (see Figure 2). Results indicate that overall performance drops drastically. While masters still maintain some superiority with game positions, they do not perform better with random and truly-random positions. CHREST simulates these results by assuming that players need to 're-centre' the pieces in their mind's eye in order to facilitate the recognition of chunks. This takes time and thus lowers performance.

Beyond chess, the chunking mechanisms embodied in CHREST have explained empirical data in other domains.[6] Within expertise research, they have accounted for computer programmers' memory and the learning of multiple representations in physics. Beyond this, they have helped model how children acquire the syntactic categories of their native language, and how humans combine information from different input modalities (see Peter Lane's contribution on page 7). Overall, CHREST shows that simple mechanisms leading to the implicit learning of a large number of chunks may underpin (expert) behaviour in a number of domains.

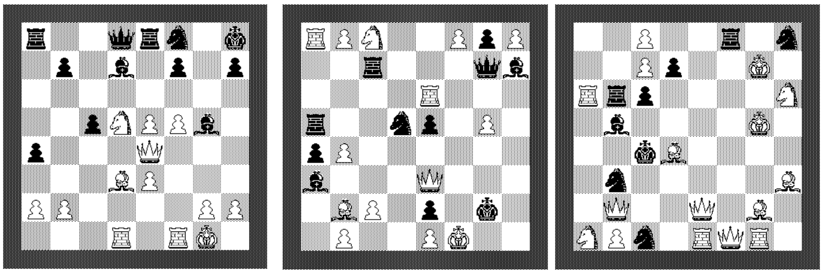

Figure 1. A game position (left), random position (middle), and 'truly random' position (right).

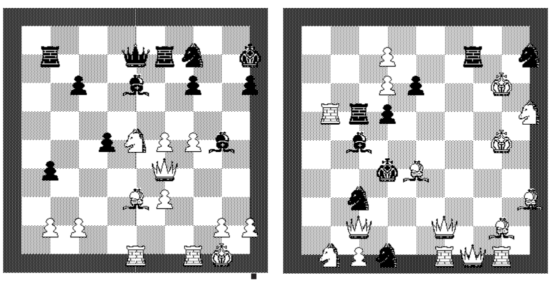

Figure 2. Positions where the pieces have been placed at the intersection of squares: a game position (left); and a truly random position (right).

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