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Intuitive Decision-Making Revisited: A Heuristic and the Feeling of Recognition

William G. Kennedy (WKennedy@GMU.Edu)
Krasnow Institute for Advanced Study, George Mason University, 4400 University Drive
Fairfax, VA 22030 USA

Abstract

At a previous International Conference on Cognitive Modeling (ICCM) a simple model of intuitive decision-making was presented. The task was to learn and then recognize strings that had a hidden structure. The model did well a matching of human performance on hits, misses, correct rejections, and false alarms. A deeper look reveals not just more details about the context and challenge of the memory task, but an explanation of the associated heuristic and the feeling of recognition.

Keywords: Intuitive decision-making; Recognition Heuristic; feeling of recognition.

Introduction

With and without conscious effort we train our subconscious mind and we can use that learning to improve performance on explicit tasks (Lehrer, 2010). This is the fundamental idea behind the bestselling books on the topic each describing many examples of the phenomena (Gladwell, 2007; Gigerenzer, 2007). Intuitive decision-making refers to implicit pattern recognition that is not thought to involve symbolic rules (Klein, 1998).

The ACT-R theory (Anderson, 2007; Anderson, et al., 2004) represents memory tasks by the building activations for the discrete, symbolic things we want to remember. The theory and architecture compares the activation of items in memory against a threshold to determine whether a retrieval attempt is successful thus making of remembered item consciously available.

A previous ICCM conference paper (Kennedy & Patterson, 2012) described a model of the process on an intuitive learning task (Reber, 1967), i.e., below the level of individual object recognition. The idea was that instead of training increasing the activation for the discrete items to be learned, another process was taking place, which noted the structure of the objects to be learned. This deeper, unconscious, intuitive learning supported the performance at the higher, explicit level. The model did very well at matching the human subjects' performance, the hits, misses, correct rejections, and false alarms. See Table 1 for updated results.

Table 1: Human and Model Performance.

Response type	Human (SEM)	Model
Hits	31.5/44(2.7)	34/44
Misses	12.5/44(2.2)	11/44
Correct Rejections	35.6/44(2.7)	39/44
False Alarms	8.4/44(2.2)	5/44

The learning and retrieval process described in the previous paper appears to be related to the Recognition Heuristic described by Gigerenzer's group (Gigerenzer, Todd, & the ABC Research Group, 1999; Gigerenzer, Hertwig, & Pachur, 2011). That Recognition Heuristic relies on a discriminatory level of recognition: one of two choices being recognized, the other not. The selection criterion is useful because it is often correlated with recognition goal. The algorithm implemented in the ACT-R model was to consider each sequential pair of letters, a bigram, in turn through to the end and for each bigram to decide. If the bigram is recognized, the next one is considered. If not, the string is not recognized. If the process reaches the end and each bigram had been recognized, then the string is considered recognized and therefore presumed to be valid.

Here I present a deeper description of the task, the training, the testing, and the performance of the human subjects and the model providing additional support for the capabilities of the ACT-R architecture to represent intuitive learning and performance with some effort by the modeler.

Deeper into the Task

At one level, the Reber task is a standard memory task with training (presentation of the objects to be remembered) followed by tests of recall of those and similar objects. However, the purpose of the scenario is not the explicit memory for the specific objects used in the training, but the development and testing of the patterns within the objects. The objects, specifically, strings of letters, have the structure presented in Figure 1. The subjects are not shown nor explicitly trained on the structure itself, but it is implicitly presented through the strings presented in training. The testing evaluates the learning of the underlying structure because the training does not present the full set of the strings to be recognized.

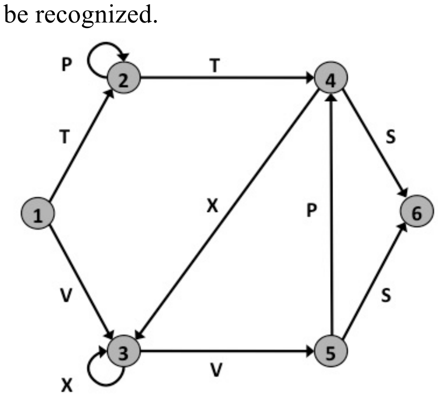

Figure 1. Finite state diagram defining a grammar of letter strings. (From Reber, 1967.)

Deeper into the Training

The training protocol presents a randomly selected set of 18 strings of length 8 or fewer. However, what needs to be learned is the structure. The ACT-R model made the structure explicit by noting the sequencing of the letters in the training strings as bigrams. In the model, each training string is treated as a series of bigrams to be learned as discrete objects (chunks) for which activations were developed.

Analysis of the grammar determined that the full set of 40 valid strings is made up of only 14 bigrams. As an example, the strings "TPPTS", "TPPPTS", "TPPPPTS", and "TPPPPPTS" are made up of only 4 bigrams: "TP", "PP", "PT", and "TS". Analysis of the number of repetitions of the 14 bigrams in 1,000 training sets of 18 strings found that all the bigrams are likely to be presented to each participant (although some with high variance) even though less than half (41%) of the full strings are included in the training.

Deeper into the Testing

The testing protocol used 22 randomly selected valid strings and 22 randomly generated invalid strings using the same letters. Each member of the test set is presented twice resulting in 44 possible hits/misses and 44 possible correct rejections/false alarms. Analysis of 1,000 sets of 22 valid strings revealed that all of the bigrams were used, but again the more rare ones having high variance.

Deeper into the Performance

The performance of the human subjects and the model can be discussed below the string level as well. The data available on the human subjects includes the specific training sets and testing sets, with performance on the test set at the individual string level. The analysis of the human and model's performance at the string and bigram levels shows the strings for each type of response (hits, misses, correct rejections, and false alarms) are very similar.

Discussion

The similarity of the performance on this task at the deeper level is further evidence that the model and the human subjects are using the same process (heuristic) to intuitively learn and decide the questions in this task. This is considered relying on intuitive or "gut" feelings because the only thing used in the ACT-R memory retrieval process is only the status of whether the retrieval was successful or not. This is a new, beyond rational representation of cognition already supported within the ACT-R theory and architecture, although the topic is not new (Lebiere & Wallach 2001). It also supports the concept of the transfer of basic cognitive skills below the symbolic level of ACT-R (Taatgen, 2013). As such, it has the potential to represent many of the variety of intuitive decisions we make every day.

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