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SRT is as easy as 12AKDB3

Sequence learning — how we learn that one event or item follows another — has been studied mostly focusing on the effects of relatively simple relationships between elements. Using network science, a new study shows that in complex probabilistic sequences, some relationships are more easily learned than others.

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When watching or participating in a favourite sport, there are advantages and enjoyment in trying to predict what move or set of moves will come next. A superstar's talent likely comes not only from what her own muscles are capable of, but also from her ability to learn and forecast the responses of her opponent. This ability, in turn, then allows her to prepare a suite of her own reactions. Thus, these sequences of movements that unfold are not deterministic; the previous movement or set of movements does not perfectly predict the next. Instead, the movements are probabilistic and groups of them may be more likely to occur together — they are probabilistically connected. While many investigations have assessed the acquisition of deterministic sequences, there is a gap in our knowledge of how the underlying structure of probabilistic sequences influences learning. Now a study by Kahn et al. reported in *Nature Human Behaviour* addresses this question using network science[1].

One common method of studying motor sequence learning is with the serial reaction time task (SRTT)[2]. In the SRTT, participants are sequentially shown stimuli that each indicate a particular button-press response. Often unbeknown to the participant, the series of button presses will form a repeating sequence. The resulting decrease in response (reaction) times, compared with button presses that are random and not part of a sequence, is a hallmark of sequential learning. This task has been used to study the features of sequence learning in both deterministic and probabilistic sequences[3] (Fig. 1a). These previous studies showed that humans were capable of learning simple structures (that is, the probability of one stimulus given another), but left open the question of what kinds of complex structures of sequences were more readily learnable, and why.

The study by Kahn et al.[1] presents a method to map the landscape of these probabilistic structures by utilizing network science. As shown in Fig. 1, the nodes and edges in graph structures represented the button presses and temporal relationships, respectively. The sequence of button presses that participants were asked to execute came from traversing the nodes of the graph. A key innovation is that the authors tested different arrangements of the nodes and edges of the graphs such that the number of connections was the same, but the structure was different (Fig. 1b). Two such structures that they compared were graphs where groups of nodes formed 'islands' with equally distributed 'bridges' between the islands (modular graphs), and graphs where the nodes formed a grid-like structure with balanced connections (lattice graphs). They found that people more readily learned the modular structure, compared with the lattice structure, as indicated by decreased reaction times. Further, they found that people were slower to transition across the 'bridges' in the modular structures. This result is striking because these 'bridge' nodes have the same probability and number of connections as nodes on the interior of the 'island'. Thus, these experiments show that these structures constrain human responses and illustrate the utility of applying network science to the study of motor-sequence learning.

The authors have framed their finding of increased reaction times at the 'bridges'

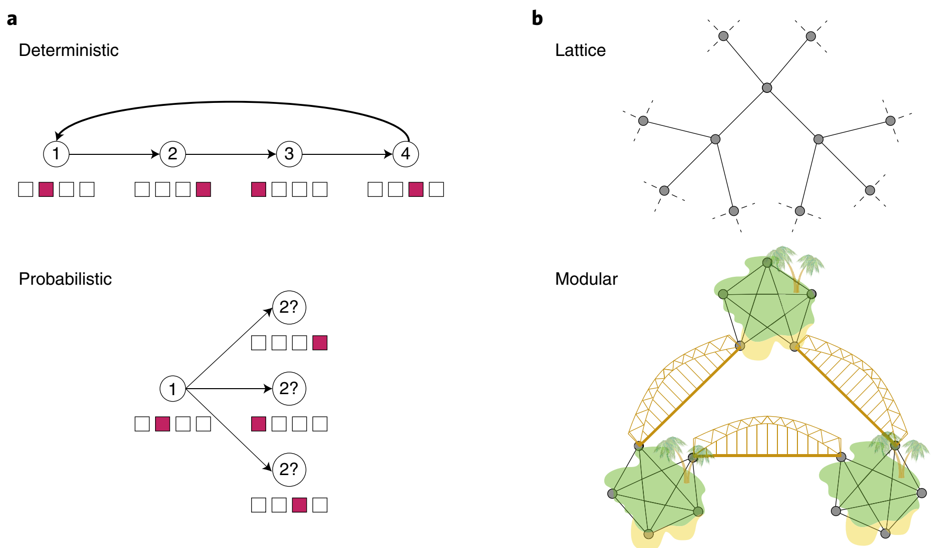

Fig. 1 | Studying sequences with network science. a, Two serial reaction time tasks. Circles indicate nodes or steps in the sequence, numbered according to their order. Arrows show the progression or transitions between the nodes. Squares below each node depict the possible button presses, and the red coloured square designates the specific button that must be pressed for each step in the sequence. In the deterministic sequence (top), the heavy black line indicates that people have greater reaction times at the start of a sequence. In the probabilistic sequence (bottom), question marks indicate that the sequence could progress to any one of those three nodes (and associated button presses) after node 1. **b**, Two graph structures used in Kahn et al.[1]. These structures constrain learning, as people show greater improvements in the modular structure. The heavy brown lines indicate that people have greater reaction times on the 'bridges' between 'islands' or modules of the probabilistic graph structure. These increased reaction times could be related to increased reaction times observed at the beginnings of deterministic sequences.

in the modular structure in terms of a 'surprisal effect'. The surprisal effect is simply defined as an increase in reaction time when going between the modules ('islands'), and has been found in previous work by this group[4]. Another possible explanation for the increased reaction times also exists, and is mentioned briefly by the authors. In motor-sequence tasks such as the SRTT, increased reaction times are often observed at the beginnings of sequences, or chunks of deterministic sequences within a probabilistic structure[3,5]. These increased reaction times, framed as a sequence initiation cost, also exist at the beginnings of more abstract sequences, such as a series of remembered categorizations to perform on serially presented stimuli (for example, colour, shape, shape, colour)[6]. In the context of these previous experiments, the increased reaction time at the beginning of the sequence was defined as a sequence initiation cost. The sequence initiation cost was taken as evidence of the action of a 'controller' in preparing for the upcoming sequence, as its properties were affected by the properties of the upcoming sequence.

While the experimental situations are somewhat different, these experiments raise the possibility that the surprisal effect and the sequence initiation cost may be related. If the processing of a controller is what is responsible for the increase in reaction time, then this increased time may be related to preparing for the upcoming movements, or sets of movements. In the previous motor sequences tasks[3,5], these subsequent movements were deterministic and therefore could be prepared for very specifically. At first examination, it may seem as though the surprisal effect may be different from sequence initiation cost in that there is an entire set of responses that are probable after the surprisal effect. However, an important feature of the initiation cost in abstract decision sequences is that the precise motor response cannot be predicted; only the categorization to be performed on the randomly presented stimulus can be predicted[6]. In this way, the sequence initiation cost can be conceptualized as preparing for a set of motor responses, as in the current study. Future work will be needed to determine whether and how the surprisal effect and sequence initiation are related.

Kahn et al. have broken new ground in illustrating the potential of network science to provide a framework with which to approach complex sequential paradigms. Further investigation will have to determine exactly why these modular structures are preferred, and what mechanisms in the brain are responsible for the observed behavioural effects. The frontal cortex has been shown to be responsible for progressively greater levels of abstract control in progressively anterior regions[7]. Therefore, a candidate region to examine may be the rostral lateral prefrontal cortex, or the frontal pole, as it has been shown to be necessary for abstract sequential control[8]. Preparing for an upcoming probabilistic set of actions may still be under the influence of cognitive control as well, perhaps in a manner that is more abstract than previously conceptualized. Regardless of the specific hypotheses, a clear challenge going forward will be relating such frameworks to the functioning of the brain, and then to the full richness of natural human behaviour. ❐

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Competing interests
The author declares no competing interests.