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Learning non-local dependencies

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Abstract

This paper addresses the nature of the temporary storage buffer used in implicit or statistical learning. Kuhn and Dienes [Kuhn, G., & Dienes, Z. (2005). Implicit learning of nonlocal musical rules: implicitly learning more than chunks. *Journal of Experimental Psychology-Learning Memory and Cognition*, *31*(6) 1417–1432] showed that people could implicitly learn a musical rule that was solely based on non-local dependencies. These results seriously challenge models of implicit learning that assume knowledge merely takes the form of linking adjacent elements (chunking). We compare two models that use a buffer to allow learning of long distance dependencies, the Simple Recurrent Network (SRN) and the memory buffer model. We argue that these models – as models of the mind – should not be evaluated simply by fitting them to human data but by determining the characteristic behaviour of each model. Simulations showed for the first time that the SRN *could* rapidly learn non-local dependencies. However, the *characteristic* performance of the memory buffer model rather than SRN more closely matched how people came to like different musical structures. We conclude that the SRN is more powerful than previous demonstrations have shown, but it's flexible learned buffer does not explain people's implicit learning (at least, the affective learning of musical structures) as well as fixed memory buffer models do.

Keywords: Implicit learning; Statistical learning; Artificial grammar learning; Chunks; Non-local dependencies; Simple Recurrent Network; Memory buffer model

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1. Introduction

Implicit or statistical learning is an incidental learning process in which people become sensitive towards structures and regularities without needing to be aware of the knowledge acquired (Cleeremans, Destrebecqz, & Boyer, 1998). A basic question concerning how such knowledge is learned is whether the learning mechanism uses a temporary storage buffer, and, if so, what the nature of the buffer is. Though fundamental, this question has been scarcely addressed in an explicit way; its answer is intimately related to specifying what contents can be implicitly learned.

Implicit learning historically has been most vigorously investigated using the artificial grammar learning paradigm (Reber, 1989), in which participants are asked to memorize a set of letter strings that have all been generated using a finite state grammar. Following this memorization phase, participants are presented with a new set of test items, half of which obey the rule used to create the training items and the other half of which violate the rule in some way. Even though participants are usually unable to describe the rules used for their decisions, their classification performance is above chance. Similar statistical learning effects have been shown in many other paradigms (see Perruchet & Pacteau, 2006, for a review), but there remains controversy over what participants have learnt, and the computational mechanism responsible for this type of learning.

To date, most results from artificial grammar learning experiments using finite state grammars can be accounted for by postulating people learn chunks of adjacent elements (e.g. Dulany, Carlson, & Dewey, 1984; Perruchet & Pacteau, 1990). This acquisition of chunks is explicitly captured by chunking models of implicit learning (e.g. Knowlton & Squire, 1994, 1996; Perruchet & Vinter, 1998; Servan-Schreiber & Anderson, 1990) and is also predicted by connectionist models of implicit learning (e.g. Cleeremans, 1993). Although several different connectionist architectures have been proposed (cf. Dienes, 1992; Kinder, 2000b), the Simple Recurrent Network (SRN) (Altmann, 2002; Elman, 1990) has become one of the most popular, based both on empirical and theoretical grounds (Kinder, 2000a). We will first present the SRN network and then the buffer memory network, two networks that operate with contrasting types of storage buffers. Then we will introduce materials that cannot be learnt by simple chunking models as they require a buffer.

2. The Simple Recurrent Network

The SRN is a three-layered feed-forward network consisting of an extra set of units (context units) which is a copy of the hidden layer from the previous time step that then feed back into the hidden layer; thus, at time t the activation of the hidden units is influenced by both the input activation and the activation of the hidden units at time $t-1$ (see Fig. 1). During the training phase, the SRN is presented with each element of the sequence and is trained to predict the next element. During this training phase the weights are updated using backpropagation. Once the SRN is trained, it becomes sensitive to the transitional probabilities between the elements of the