Randomly Changing Transfer in Artificial Grammar Learning

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In the artificial grammar learning (AGL) *transfer* paradigm Ss are instructed to memorize a set of strings, which (unbeknownst to them) were generated by a finite state grammar. They are then informed that the strings followed by a set of rules, and asked to categorise novel strings as following or violating those rules. Unlike the standard paradigm (Reber, 1967), the novel strings are composed from a different "alphabet" from the training strings, although the underlying rules are unchanged. Ss are nevertheless able to make the required distinction at above chance (and control) levels.

The transfer phenomenon is the primary evidence for Reber's claim that in AGL Ss acquire representations which are *abstract*, both with respect to individual training items, and also to the surface features (*e.g.* particular letters) of those items.

Whittlesea and Dorken (1993) provide apparently stronger evidence for abstract representations. They changed the test alphabet randomly for every single test item. However, the near-chance performance of their Ss (.53) is not conclusive without comparison against a proper control, such as a group of untrained Ss.

We trained Ss as standard, and tested their performance in a randomly changing transfer test (condition RandTransfer). An untrained group (RandControl) was tested in this condition, to provide an appropriate baseline. We also ran 3 other conditions: Standard (no letter set change), Transfer (a single change of letter set between training and test), and Control (no training, with the same letter set throughout testing).

An additional factor was that the test strings were either composed of the 20 training strings, plus 5 novel strings (the Same condition), or of 20 novel strings, and 5 of the training strings (Different). This tested the effect of similarity to memorised whole exemplars; identical items must be highly similar, and the Same Ss should perform better. Stimuli were taken from the "standard" grammar (see Redington & Chater, 1994).

Prior to making each grammaticality judgement, Ss also performed a guessing game, reconstructing the test item by guessing each letter in turn. The procedure closely followed that used in Redington & Chater, 1994).

Grammaticality judgment results (see Table 1) indicated reliable transfer, in both Transfer and RandTransfer conditions. Same Ss did not perform reliably better than Different (largely novel test strings) Ss, in either the Standard or transfer conditions. Guessing game (prediction) performance generally mirrored the above pattern of results, although there was a marginally reliable overall effect for the Same/Different manipulation, probably due to the similarity between training and test strings at the fragment level.

Condition	n	Score	Comparison	p
Control	10	.56 (.06)	.5	$>.01$
Standard	20	.68 (.08)	Control	.0002
Transfer	20	.60 (.06)	Control	.0005
RandControl	10	.53 (.06)	.5	.07
RandTransfer	20	.59 (.09)	RandControl	$>.05$

Table 1: Mean grammaticality judgment scores (standard deviations in parentheses), and comparisons (1-tailed t-tests) against the appropriate controls

Above control RandTransfer performance might be taken as strong support for abstract representations. We suggest that transfer generally is equally well explained by the acquisition of surface-based knowledge, and processes of abstraction between old and new surface forms *at test*. Simple models working on this basis can capture the transfer phenomena demonstrated here (Redington & Chater, in press).

Reber (1969) presents the only evidence which unequivocally supports an abstract knowledge account. Ss memorising rule-governed strings maintained a memorisation advantage across letter sets, suggesting that they were encoding the strings' structure independently of surface form. Redington and Chater's simple models cannot capture this effect. Our current research is therefore concerned with replicating, or falsifying, this theoretically crucial phenomenon.

References

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