# Modality transfer of acquired structural regularities:

# A preference for an acoustic route

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**Abstract**

Human implicit learning can be investigated with implicit artificial grammar learning, a simple model for aspects of natural language acquisition. In this paper we investigate the remaining effect of modality transfer in syntactic classification of an acquired grammatical sequence structure after implicit grammar acquisition. Participants practiced either on acoustically presented syllable sequences or visually presented consonant letter sequences. During classification we independently manipulated the statistical frequency-based and rule-based characteristics of the classification stimuli. Participants performed reliably above chance on the within modality classification task although more so for those working on syllable sequence acquisition. These subjects were also the only group that kept a significant performance level in transfer classification. We speculate that this finding is of particular relevance in consideration of an ecological validity in the input signal in the use of artificial grammar learning and in language learning paradigms at large.

**Keywords:** Artificial grammar learning; Implicit learning; Modality transfer

## Introduction

Humans possess adaptive mechanisms capable of implicitly extracting structural information solely from observation (Stadler & Frensch, 1998), as indicated by for example artificial grammar learning. Reber (1967) suggested that humans can learn artificial grammars implicitly by an abstraction process intrinsic to natural language acquisition. Natural language is an example of the infinite use of finite means. The simplest relevant formal model incorporating this idea is represented by the family of right-linear phrase structure grammars, which can be implemented in the finite-state architecture, are typically used in artificial grammar learning.

Natural language acquisition is a largely spontaneous, non-supervised, and self-organized process. The structural aspects of natural language are acquired at an early age largely without explicit feedback (Jackendoff, 2002) while reading and writing are examples of typically explicitly taught cognitive skills. Implicit learning has four characteristics: (1) no or limited explicit access to the acquired knowledge; (2) the acquired knowledge is more complex than simple associations or exemplar-specific frequency-counts; (3) is an incidental consequence of information processing; and (4) does not rely on declarative memory (Forkstam & Petersson, 2005). Implicit learning as used in the artificial grammar learning paradigm is a process whereby a complex, rule-governed knowledge base is acquired largely independent of awareness of both the process and product of acquisition.

Recently, the artificial grammar learning paradigm has been proposed as a model for aspects of language acquisition (Gomez & Gerken, 1999) and for exploring differences between human and animal learning relevant to the faculty of language (Hauser et al., 2002). Evidence from functional neuroimaging data is consistent with this suggestion. Brain regions related to natural language syntax are also engaged in artificial syntactic processing. In particular, the left inferior prefrontal cortex centered on Broca's region (Brodmann's area 44/45) is sensitive to artificial syntactic violations (Forkstam, Hagoort, Fernandez, Ingvar, & Petersson, 2006; Petersson, Forkstam, & Ingvar, 2004). Moreover, this region is specifically sensitive to the structural properties rather than to local linear surface features of the input items.

In the current study we investigated the difference in the lasting effects of artificial grammar learning in a modality transfer over the visual/acoustic signal relevant to the language function distinction over reading/listening, using working on either orthographically represented letter sequence (cf. e.g., Forkstam, Elwér, Ingvar, & Petersson, 2008) and acoustically represented syllable sequences (cf. e.g., Faísca, Bramão, Forkstam, Reis, & Petersson, 2007), respectively. We used an implicit acquisition paradigm without feedback in which the participants were only exposed to positive examples (i.e., well-formed consonant strings) generated by the Reber grammar. We used a between subject design with two groups practicing on either acoustically or visually presented sequences. Classification strings were balanced for substring familiarity relative the acquisition string-set, independent of grammatical status. In order to keep the similarity over modality as tight as possible were the strings presented in a sequential fashion for both the acoustically presented syllables and the visually presented consonant letter strings. To minimize the influence of explicit knowledge and explicit strategies were the subject never informed during the acquisition about the underlying structure in the acquisition strings. Partly for the same purpose we used repeated short-term memory tasks extending over 5 days as prolonged acquisition over several days has shown still increasing performance in artificial grammar learning in (Forkstam et al., 2008). After the last acquisition session on day 5 were the subjects informed about the existence of the grammatical structure in the acquisition input and instructed to perform grammaticality classifications on new strings similar to the acquisition strings. This first grammaticality classification test was performed in the same modality as during acquisition and was followed by a second grammaticality classification performed in the transfer modality.

## Implicit statistical learning

A complementary perspective on artificial grammar learning views this as a model for investigating implicit learning (Forkstam & Petersson, 2005). Reber (1967) defined implicit learning as the process by which an individual comes to respond appropriately to the statistical structure inherent in the input. Thus, he argued, the capacity for generalization that the participants show in grammaticality classification is based on the implicit acquisition of structural regularities reflected in the input sample. Reber (1967) suggested that humans acquire implicit knowledge of the underlying structure through an inductive statistical learning process and that this knowledge is put to use during classification. Support for the implicit character of artificial grammar learning comes for example from lesion studies on amnesic patients. Knowlton and Squire (1996) investigated amnesic patients and normal controls on a classical and a transfer version of the artificial grammar learning task. The patients and their normal controls performed similarly on both artificial grammar learning tasks while the amnesic patients showed no explicit recollection of whole-item or fragment (i.e., bi- or tri-gram) information. Based on the results from the transfer version they argued that artificial grammar learning depends on the implicit acquisition of both abstract and exemplar-specific information. Knowlton and Squire (1996) suggested that the latter indicates that distributional information of local sequential regularities is acquired, while the former suggests that abstract (i.e., 'rule-based') representations are also acquired. Moreover, recent studies provide evidence that rapid (on the order of 2 – 10 min) 'rule-abstraction' (Marcus, Vijayan, Bandi Rao, & Vishton, 1999), learning of transition probabilities in artificial syllable sequences (Saffran, Aslin, & Newport, 1996), and artificial grammar learning (Gomez & Gerken, 1999) also occur in young infants. Furthermore, the study of Gomez and Gerken (1999), also demonstrated that infants can show some transfer capacity, suggesting that they were abstracting beyond the acquisition material. In addition, learning of long distance dependencies has been demonstrated in both sequence learning paradigms as well as in artificial grammar learning (Ellefson & Christiansen, 2000). Moreover, it has been suggested that induction cannot be explained entirely in terms of the acquisition of local sequential regularities (Meulemans & Van der Linden, 1997). Thus, while Reber (1967) originally argued that the implicit learning process abstracted 'rule-based' knowledge (see Reber, 1993 for a modification of his position ), these more recent studies suggest that dual mechanisms may be at play (cf. e.g., Forkstam & Petersson, 2005).

## The Reber grammar

In general, formal (artificial) grammars serve as an intentional definition of languages. These represent the formal specification of mechanism(s) that generate various types of structural regularities (cf. e.g., Davis, Sigal, & Weyuker, 1994), and they are relevant for any cognitive domain which engages processes operating on structured representations, including for example the temporal organization of actions (i.e. planning), language, and perception/generation of musical sound patterns (Petersson et al., 2004). A formal grammar, as the one used in this artificial grammar learning study, thus represents a specification of a finite generating/recognizing mechanism for a particular language; in our case the Reber language. Thus, the transition graph representation of the Reber machine (Figure 1) is an explicit generating and recognition mechanism for the Reber language (e.g., Davis et al., 1994).

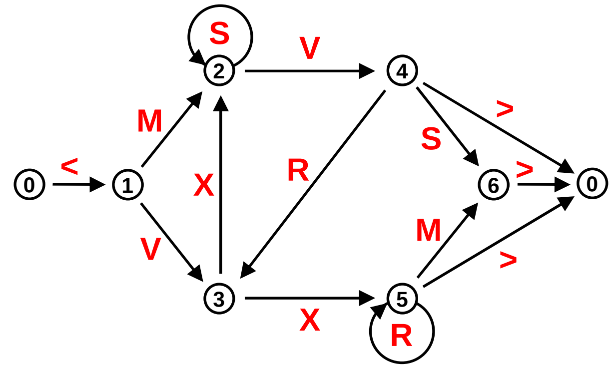


**Figure 1**: The Reber grammar is an example of a right-linear phrase structure grammar which can be implemented in a finite-state architecture, here represented by its transition graph. Grammatical strings are generated by traversing the transition graph from state 0 through the internal states along the indicated direction until reaching an end state. The grammar will e.g. generate/parse <MSSVRXSV> as a grammatical string but not the non-grammatical string <MXSVRXVV>.

## Experimental design

In the present study we employed the implicit artificial grammar learning paradigm to investigate the difference in the lasting effects of artificial grammar learning in a modality transfer over the visual/acoustic signal relevant to the language function distinction over reading/listening. We used a between subject design with two groups practicing on either orthographically represented letter sequence or acoustically represented syllable sequences. We used an implicit acquisition paradigm without feedback in which the participants were only exposed to positive examples (i.e., well-formed consonant strings) generated by the Reber grammar (**Figure 1**).

25 right-handed healthy university students volunteered to participate in the study (14 females, mean age = 26 years, range = 20-36 years). They were all pre-screened for medication use, history of drug abuse, head trauma, neurological or psychiatric illness, and family history of neurological or psychiatric illness. Written informed consent was obtained according to the Declaration of Helsinki and the local medical ethics committee approved the study. Eleven of the participants were included in the syllable group and 14 participants in the consonant letter group.

The strings presented in a sequential fashion for both the acoustically presented syllables and the visually presented consonant letter strings during acquisition as well as classification. The sequences presented in the acoustic modality were generated from a set of normally occuring syllables in Swedish (i.e., {bå, fe, lu, pa, ti}) while the visual presented sequences were generated from a consonant letter alphabet (i.e., {M, S, V, R, X}). The sequences were presented in a sequential order 300 ms on 300 ms off in both modalities using the Presentation software (nbs.neuro-bs.com).

Before the first acquisition session, and in the same modality as during acquisition, did the participants perform in baseline preference classification where they indicated if they liked a string or not based on their immediate intuitive impression (i.e., guessing based on “gut feeling”.

During each acquisition phase for each of the 5 days, to keep the structural information of the stimulus material covert to the participants, were the participants engaged in repeated short-term memory task without performance feedback. They were presented in a self-paced fashion with pairs of either syllable sequences or consonant letter strings from the acquisition sample generated from the Reber grammar and had to respond whether the sequences were the same or different immediately after presentation.

After the last acquisition session on day 5 were the subjects informed about the existence of a complex system of rules used to generate the acquisition strings (but were not informed about the actual rules) and instructed to classify novel strings generated from the same system of rules as the acquisition strings as grammatical or non-grammatical based on their immediate intuitive impression (i.e., guessing based on ‘’gut feeling’’). This first grammaticality classification test was performed in the same modality as during acquisition and was immediately followed by a second grammaticality classification performed in the transfer modality. The classification string sets were balanced for substring familiarity relative the acquisition string set, independent of grammatical status.

### Stimulus Material

Grammatical strings with a string length of 5-12 were generated from the Reber grammar. The frequency distribution of bi- and trigrams (2 and 3 letter chunks) for both terminal and whole string positions were calculated for each string in order to derive the associative chunk strength (ACS) for each item (cf., Meulemans & Van der Linden, 1997). An acquisition set was selected as well as grammatical and non-grammatical classification test strings. The non-grammatical strings were generated by a switch of letters in two non terminal positions in a grammatical string. The classification set was further divided into high and low ACS items relative the acquisition string set. We thus manipulated two independent stimulus factors with respect to the classification set, grammaticality (grammatical/non-grammatical) and ACS (high/low) in a 2x2 factorial experimental design.

It has been argued that sensitivity to the level of ACS is a reflection of a statistical fragment-based learning mechanism while sensitivity to grammaticality status independent of ACS is related to a structure-based acquisition mechanism (Knowlton & Squire, 1996; Meulemans & Van der Linden, 1997). Consequently, it has been argued that sensitivity to ACS reflects an explicit declarative learning mechanism while sensitivity to grammaticality status independent of ACS reflects an implicit procedural learning mechanism.

### Data analysis

Mixed-effect repeated measures ANOVAs were used for the analysis of the classification performance translated to d-prime over both factors grammaticality and ACS using standard signal detection theory in the statistics package R (www.r-project.org). For each analysis we modeled the main factors classification session [within modality/between modality] as within subjects fixed-effects, group [acoustic/visual] as between subjects fixed-effect, and subjects as random-effects. An overall significance level of $P < 0.05$ was used for statistical inference, and explanatory investigations for significant effects were restricted to the reduced ANOVA contrasted over the appropriate factor levels.

## Results

### Classification Performance

**The Syllable group** showed significant grammaticality sensitivity in the within modality syllable classification (85% performance level; $F(1, 10) = 137$, $P < 0.001$) and managed also to transfer into the visual modality (62%; $F(1, 10) = 19$, $P = 0.001$; **Figure 1** & **2**). A static substring sensitivity persisted throughout acquisition from the baseline preference classification ($F(1, 9) = 6.2$, $P = 0.032$) to the last day grammaticality classification ($F(1, 10) = 15$, $P < 0.003$) but then disappeared in the transfer modality classification ($P > 0.25$; **Figure 3**).

**The consonant letter group** lso showed significant grammaticality sensitivity in the within modality consonant classification (68% performance level; $F(1, 13) = 25$, $P = 0.001$) but failed to transfer into the acoustic modality (52%; $P > 0.19$; **Figure 1** & **2**). A static substring sensitivity persisted throughout transfer from the within modality classification ($F(1, 13) = 60$, $P < 0.001$) to the transfer acoustic modality ($F(1, 13) = 23$, $P < 0.001$; **Figure 3**).

**Between group effects** persisted for grammaticality sensitivity where the syllable group performed better on the within modality test ($F(1, 22) = 20$, $P < 0.001$) and between modality ($F(1, 22) = 10$, $P = 0.004$), indicating a persisted transfer effect for the syllable group as opposed to the consonant group random performance. No difference between group in substring sensitivity transfer was found ($P > 0.08$).

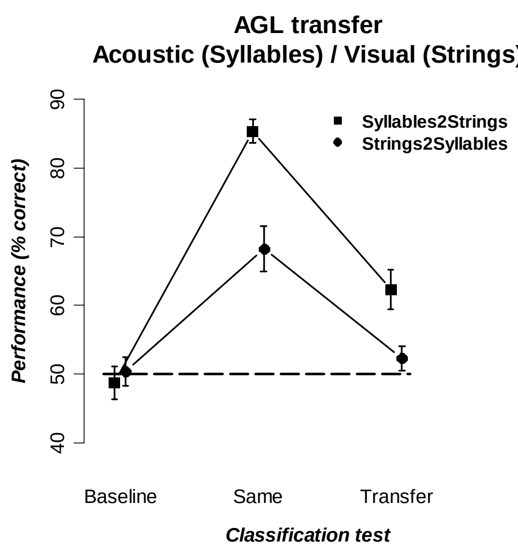


**Figure 2**: Percent correct data for the syllable and consonant string group. Error bars correspond to the standard error of the mean.

## Discussion

In the present study we employed the implicit artificial grammar learning paradigm to investigate the difference in the lasting effects of artificial grammar learning in a modality transfer over the acoustic/visual signal. In grammaticality classification after 5 days of implicit acquisition both subjects which had practiced on acoustically presented syllables and subjects which had practiced on visually presented consonant letter strings showed high performance levels (**Figure 2**). However, when tested in cross-modality did only participants which had acquired the acoustical syllable sequences (the equivalence to the language function listening signal) manage to show significantly transfer performance to the orthographically represented letter sequences (equivalent to the reading signal) of the grammatical structure and not vice versa. We believe this finding implicates a relevance of ecological validity in the input signal in the use of artificial language paradigms such as artificial grammar learning, and potentially also in language learning paradigms at large.

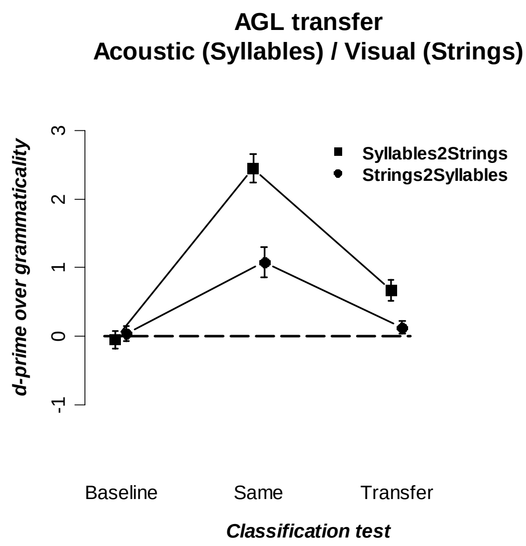


**Figure 3**: D-prime as a function of grammaticality status for the syllable and consonant string group.

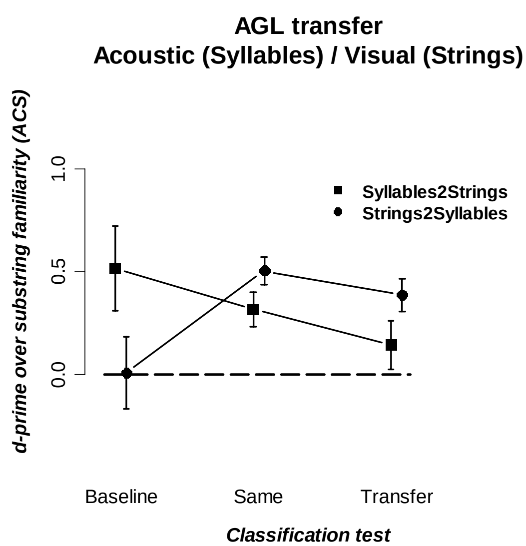


**Figure 4**: D-prime as a function of substring familiarity (ACS) status for the syllable and consonant string group.

Most studies reporting successful transfer using the artificial grammar learning paradigm have been working within the visual modality and in specific with letter sequences (Gomez & Schvaneveldt, 1994; Reber, 1969). Transfer over letter alphabet has also successfully shown lasting effects of transfer in amnesic patients (Knowlton & Squire, 1996). Within transfer investigation in the acoustic modality have also shown successful performance in 8-month-old infants in the transfer from linguistic to non-linguistic input (Malmberg, 2004). Few studies have reported strong (if any) cross-modality transfer effects. Altmann, Dienes & Goode (1995) and Bigand, Perruchet & Boyer (1998) showed successful transfer from musical tones to letters sequences, and Altmann and colleagues (1995) found also successful transfer from acoustical syllables to graphic symbols as well as from graphical symbols to written syllables.

## Grammar learning

As previously introduced, Reber (1967) defined implicit learning as the process by which an individual comes to respond appropriately to the structure in the input ensemble. Thus, he argued, the capacity to generalize is based on implicit acquisition of structural regularities reflected in the input sample. However, alternative theoretical frameworks have questioned the abstract ('rule') acquisition interpretation and instead suggest that grammaticality classification utilizes exemplar-based (Vokey & Brooks, 1992) or, alternatively, is based on chunk (n-gram) representations (Perruchet & Pacteau, 1991). Thus, grammar learning, whether natural or artificial, is commonly conceptualized either in terms of structure-based ('rule') acquisition mechanisms or statistical learning mechanisms. Some aspects of natural language (e.g., syntax) are amenable to an analysis within the classical framework of cognitive science, which suggests that isomorphic models of cognition can be found within the framework of Church-Turing computability (Davis et al., 1994). These language models typically allow for a greater structural expressivity than can be (strictly) implemented in the finite-state architecture. The finite-state architecture supports unlimited concatenation recursion and can support finite recursion of general type. These latter aspects are also characteristic for human performance. From a neurophysiological perspective, it seems natural to assume that the brain is finite with respect to its memory organization. Now, if one assumes that the brain implements a classical model of language, then it follows immediately from the assumption of a finite memory organization that this model can be implemented in a finite-state architecture, although a context-sensitive or any other suitable formalism might be used as long as the finite memory organization is appropriately handled (Petersson, 2005; Petersson et al., 2004).

## Lexicalization

Prefrontal functions are commonly formulated within a framework of cognitive control and executive attention. Prefrontal working memory functions include on-line short-term sustainability of representations ('maintenance', e.g., Baddeley, Gathercole, & Papagano, 1998) processing and integration of structured information ('manipulation' and 'selection'), as well as monitoring and inhibition (Mesulam, 2002). A simple formalization of some aspects of these ideas takes advantage of the fact that hierarchically structured information can be represented in terms of nested bracketed expressions or hierarchically structured trees (Petersson, 2005; Petersson, Grenholm, & Forkstam, 2005). If one assumes that these representations are recursively constructed from more primitive structures stored in long-term memory, one possibility is to interpret integration of structured information as resulting from the retrieval of simple long-term memory representations for on-line incremental integration by successive merging of primitive structures ('unification').

Returning to the issue of grammar learning, it is possible to take a view that is placed somewhere between the two more common conceptualizations. For example, the generative mechanism of the Reber machine is easily translated into a Minimalist-type or unification-based framework (Chomsky, 1995; Joshi & Schabes, 1997). Given a transition from state $s_j$ to $s_k$ when the terminal symbol $T$ is recognized ($s_j \rightarrow T\ s_k$ in the transition graph), this would translate into a lexical item or feature vector $[s_j, T, s_k]$, where $s_j$, $T$, and $s_k$ should be interpreted as 'syntactic' features (e.g., 'specifier' feature $s_j$, and 'complement' feature $s_k$) and $T$ as a 'surface' or 'phonological' feature. A finite transition graph thus generates a finite number of lexical items. The syntactic features of these representations could very well be generated or estimated based on a statistical learning mechanism. Moreover, there is no need for a specific 'rule' acquisition mechanism, because the parsing process might use general structure integration mechanisms already in place for merging or unifying structured representations (e.g., in the left inferior frontal region), as suggested in Petersson et al. (2004). Here, two lexical items, $[s_i, R, s_j]$, $[s_k, Q, s_l]$, are allowed to unify if and only if $s_j = s_k$, or $s_l = s_i$. Note also that the syntactic features have acquired a particular functional role in this picture. This can be described in terms of monitoring or governing of the integration process based on selecting the pieces of information that can be merged. In other words, the finite-state control has been distributed over the mental lexicon (long-term memory) among the lexical items in terms of control features. This view is more akin to lexical acquisition in that it suggests that simple structured representations are created (i.e., lexical items $[s_j, T, s_k]$) during acquisition. In essence, this re-traces a major trend in theoretical linguistics in which more of the grammar is shifted into the mental lexicon and the distinction between lexical items and grammatical rules is beginning to vanish (cf. e.g., Jackendoff, 2002; Joshi & Schabes, 1997; Vosse & Kempen, 2000).

This picture provides an alternative view on artificial grammar learning that is placed somewhere between the two more common conceptualizations in terms of a rule-based acquisition or a statistical fragment (surface) based learning mechanism. Instead, the 'lexicalized' picture suggests that the acquisition of simple structured representations is akin to lexical learning and might be supported by statistical learning mechanisms. These representations are then activated, by for example an input string, and actively represented and integrated in working memory during parsing. The latter process is dependent on general integrative mechanisms in the left inferior frontal cortex, and is further dependent during automaticity of this integration process on the head of the caudate nucleus.

# Conclusion

Subjects practicing on acoustical syllables as well as subjects practicing on visual consonant letter strings showed high performance levels after 5 days of implicit acquisition. However, when tested in cross-modality did only participants working on syllables show successful transfer performance, while participants working on letter sequences did not. We speculate this to be of particular relevance in consideration of an ecological validity in the input signal in the use of artificial grammar learning and in language learning paradigms at large.

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