Syntactic Classification of Acquired Structural Regularities

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Abstract

In this paper we investigate the neural correlates of syntactic classification of an acquired grammatical sequence structure in an event-related FMRI study. During acquisition, participants were engaged in an implicit short-term memory task without performance feedback. We manipulated the statistical frequency-based and rule-based characteristics of the classification stimuli independently in order to investigate their role in artificial grammar acquisition. The participants performed reliably above chance on the classification task. We observed a partly overlapping corticostriatal processing network activated by both manipulations including inferior prefrontal, cingulate, inferior parietal regions, and the caudate nucleus. More specifically, the left inferior frontal BA 45 and the caudate nucleus were sensitive to syntactic violations and endorsement, respectively. In contrast, these structures were insensitive to the frequency-based manipulation.

Keywords: Artificial Grammar; Functional Neuroimaging; FMRI; Inferior Frontal Cortex; Caudate Nucleus.

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 (AGL). Reber (1967) suggested that humans can learn artificial grammars implicitly by an abstraction process intrinsic to natural language acquisition. Chomsky, following von Humboldt, suggested that 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 (FSA), are typically used in AGL.

It has recently been suggested that AGL is a relevant model for investigating aspects of language learning in infants (Gomez & Gerken, 2000), and second language learning in adults (Friederici, Steinhauer, & Pfeifer, 2002). Recent functional magnetic resonance imaging (FMRI) results indicate that language related brain regions are engaged in artificial grammar processing (Petersson, Forkstam, & Ingvar, 2004) and a number of FMRI studies have investigated implicit learning of material generated from artificial grammars (e.g., Seger, Prabhakaran, Poldrack, & Gabrieli, 2000; Skosnik et al., 2002). For example, Petersson et al. (2004) investigated a grammaticality classification task using 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. The results showed that artificial syntactic violations activated Broca’s region (Brodmann’s area (BA) 44/45). In the current study we tested the validity of this finding in a modified experimental design, using classification strings that were balanced for substring familiarity relative the acquisition string-set, independent of grammatical status; and sequential instead of whole string presentation paradigm for the strings.

Implicit statistical learning

A complementary perspective on AGL 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 AGL 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 AGL task. The patients and their normal controls performed similarly on both AGL 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 AGL 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 formed. 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 AGL (Gomez & Gerken, 1999) also occur in young infants. Furthermore, the study of Gomez and Gerken (1999) also demonstrated that infants 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 as well as in AGL (Ellefson & Christiansen, 2000; Poletiek, 2002). Thus, it has been suggested that induction cannot be explained entirely in terms of the acquisition of local sequential regularities (Meulemans & Van der Linden, 1997), and 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 (Chomsky, 1986). These represent the formal specification of mechanism(s) that generate various types of structural regularities (cf. e.g., the Chomsky hierarchy, 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, 2005a; Petersson et al., 2004). A formal grammar, as the one used in this AGL study, thus represents a specification of a finite generating/recognizing mechanism for a particular language; in our case the Reber language. The transition graph representation of the Reber machine (Figure 1) is thus an explicit generating and recognition mechanism for the Reber language (e.g., Davis et al., 1994).

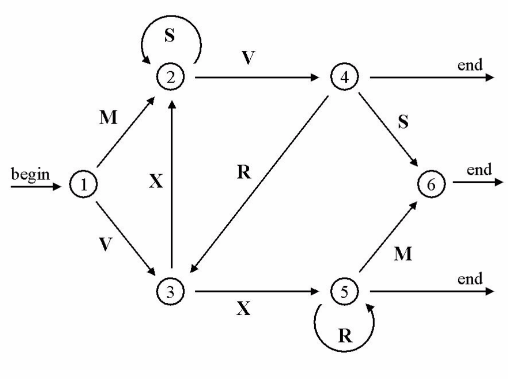

Figure 1: The Reber grammar is an example of a right-linear phrase structure grammar. This can be implemented in a finite-state architecture, here represented by its transition graph (cf., Reber & Allen, 1978).

Experimental design

In the present event-related FMRI study we employed a modified AGL paradigm. As in the classical AGL paradigm there were both acquisition and classification phases, but with the modification that the participants participated in repeated acquisition phases over 8 days. During each acquisition phase, the 12 participants (dutch-speaking with university background, 8 females, mean age ± sd = 23 ± 3 years) were engaged in a short-term memory task without performance feedback. They were presented with letter strings from an acquisition sample generated from the Reber grammar and had to retrieve these by typing each string on a keyboard immediately after presentation. The participants were informed before the acquisition session on day 1 that they would be asked to classify (i.e., guess based on 'gut feeling') new items as grammatical (G) or non-grammatical (NG), subsequent to the acquisition sessions on day 1 and day 8. EPI-BOLD FMRI data were acquired (TR = 2.8 s and 3.5x3.5x3.5 mm3 resolution; at 3T) during the classification sessions on day 1 and 8.

Grammatical strings of 5-12 consonants 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., Knowlton & Squire, 1996; Meulemans & Van der Linden, 1997). An acquisition set was selected as well as G and NG classification test strings. The NG strings were generated by a switch of letters in two non terminal G-string positions. 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 (G/NG) and ACS (H/L) 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 dependent on the medial temporal lobe (cf. e.g., Opitz & Friederici, 2003; Strange, Henson, Friston, & Dolan, 2001), while sensitivity to grammaticality status independent of ACS reflects an implicit procedural learning mechanism, which might be dependent on the interaction between prefrontal regions and the basal ganglia.

Data analysis

The FMRI data was pre-processed and anatomically normalized to a common stereotactic space, and statistically analyzed with a mixed effect procedure to allow for group level inferences in a factorial ANOVA design with non-sphericity correction. Statistical inference was based on relevant condition contrasts (correct trials only) and we used the supra-threshold cluster-size test-statistic using a significance level of $P < 0.05$ corrected for multiple non-independent comparisons based on the family-wise error rate (Worsley et al., 1996). We explored the observed local maxima in the omnibus F-test (i.e. effects related to grammaticality and ACS manipulations, for within and between test days) with a region of interest (ROI) analysis.

Results

The behavioral results showed a significant sensitivity on both test days to grammaticality ($F(11, 36) > 49$, $P < 0.001$) and ACS ($F(11, 36) > 19$, $P < 0.001$) while the interaction was non-significant. We also observed a significant increase in sensitivity to grammaticality over test days ($F(11, 84) = 117$, $P < 0.0001$; Figure 2). In contrast, this was not the case for ACS. Thus, already on the first classification test, most of the participants classified items reliably above chance and their performance improved with repeated acquisition sessions (Figure 2).

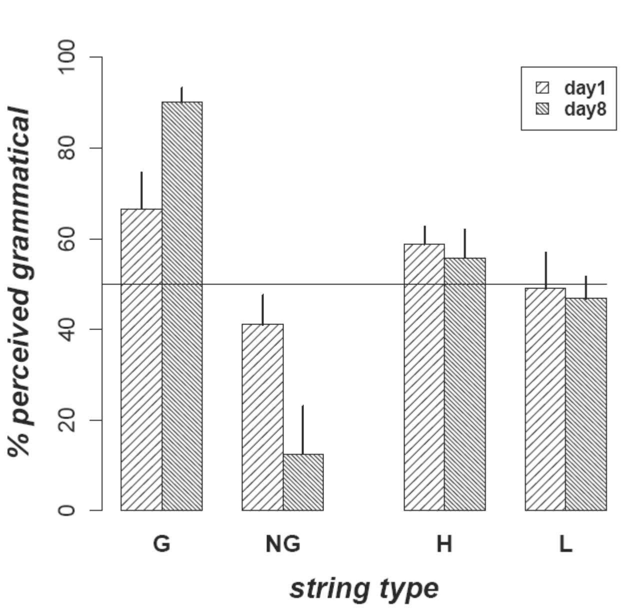

Figure 2: Endorsement grammaticality rates as a function of grammaticality status (G = grammatical, NG = non-G) as well as associative chunk strength (H = high, L = low). Error bars correspond to one standard deviation.

The FMRI results showed that the grammaticality classification in comparison to baseline activated a similar set of brain regions during both day 1 and 8. A subset of this network was significant with respect to the omnibus F-test including the factors: grammaticality, ACS, and test day. This subset included regions in the ventrolateral prefrontal cortices bilaterally, centered on inferior frontal (BA 45/47) extending into middle frontal cortex (BA 46) and frontal operculum/anterior insula (BA 47). It further included regions in the anterior (BA 24/32) and posterior cingulate (BA 23/31), the right inferior parietal (BA 39) and superior temporal (BA 22) cortex, as well as the head of the caudate nucleus, bilaterally (Table 1, left; see also Figure 3 for regions sensitive to grammaticality status).

Table 1: Local maxima of significantly activated clusters in the omnibus F-test (threshold: $P = 0.05$, false discovery rate (FDR) corrected). Right part of the table describes the post-hoc ROI analysis of the observed local maxima (radius = 5 mm). G = grammatical string; NG = non-G; ACS = associated chunk strength; H = high ACS; L = low ACS; BA = Brodmann's area; significant interactions during test day 1 (†) or 8 (‡).

Region (BA)	Z_{99}	x	y	z	ACS		GRAM		
					d1	d8	d1	d8	
L 45	4.2	-45	24	18			NG	NG	‡
L 47	4.3	-33	18	-9	L		NG	NG	
R 46	4.2	45	27	21	L	L	NG	NG	
R 47	5.4	33	21	-6	L		NG	NG	
R 32	4.5	6	27	33	L		NG	NG	
R 39	3.5	54	-51	33			NG		†
R 22	3.4	51	-48	18		L	NG	NG	
L 23/31	3.5	-12	-51	30	H			G	
31	4.1	0	-30	45	H		G	G	
NC	3.7	3	15	-3	H			G	
R hipp		28	-30	-2		L			
L hipp		-28	-30	-2	H	L			

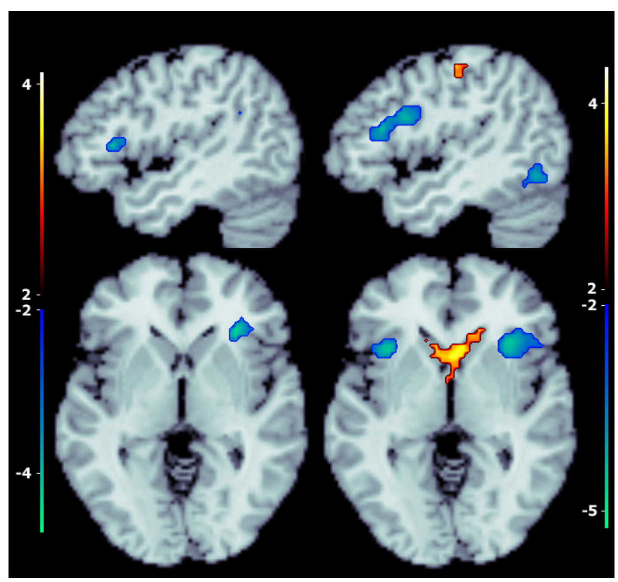

Figure 3: Regions significantly sensitive to grammatical status (G > NG in red, NG > G in blue; correct responses only). Left: test day 1. Right: test day 8. Threshold corresponding to $P = 0.05$ corrected for false discovery rate. ($x = -45$; $z = -3$).

In the ROI analysis of the network outlined above (Table 1, right), the left BA 45 was specifically and selectively sensitive to NG vs. G strings on both day 1 and 8. However, this was not the case for the ACS manipulation. Interestingly, the right inferior frontal (BA 45/46/47) and the anterior cingulate cortices (BA 32) regions were sensitivity to the level of ACS on test day 1. On test day 8, this was also the case for some right inferior frontal regions. Furthermore, the caudate nucleus was sensitive to G vs. NG strings on day 8. Finally, we observed hippocampal activations bilaterally related to the ACS manipulation on both test days (the MTL target regions were derived from a similar AGL study of Lieberman, Chang, Chiao, Bookheimer, & Knowlton, 2004).

Structural vs. fragment knowledge

We then investigated performance and regional specificity with respect to structural vs. fragment knowledge. More specifically, we investigated the performance differences between low ACS grammatical (LG) and high ACS non-grammatical strings (HNG). Correct classification of the LG items depend maximally on the grammaticality status while the support from ACS information (if used at all) is minimized and hence this should maximize the sensitivity to structurally ('rule') based processes. Conversely, classification of the HNG items depend on the ACS status while the grammaticality status works in the opposite direction and hence correct classification maximizes the utilization of fragment or frequency based knowledge. This suggests that the LG vs. HNG contrast is selective for structurally based processes, while the HNG vs. LG contrast is selective for fragment/frequency based processes.

In the behavioral data, we observed a clear preference for LG over HNG strings during test day 8 (only a trend during test day 1). This result lends support to the notion that structural (syntactic) regularities are used independent of fragment/frequency features during grammaticality classification. With respect to the FMRI data, we observed a significant caudate nucleus activation on day 8 (LG > HNG; x/y/z = 3/18/-3, cluster P = 0.023, Z99 = 4.3), suggesting that this region is selectively sensitive to structural processing. Conversely, we found the right frontal operculum to be significantly more sensitive to ACS (HNG > LG; BA 47, x/y/z = 36/24/-6, cluster P = 0.04, Z99 = 3.4), indicating that this region is related to fragment/frequency based processing.

Discussion

A primary objective of the present study was to replicate our previous finding (Petersson et al., 2004) showing that the left inferior frontal cortex (BA 44/45) is sensitive to artificial syntactic violations, using a 2x2 factorial design with substring familiarity (ACS; high/low) relative to the acquisition string set and grammatical status (G/NG) as factors, as well as using a sequential instead of whole string presentation paradigm. This was indeed the case, although the activated frontal regions were more extensive in the present study and also included right homotopic regions. However, the left inferior frontal gyrus (BA 45) was the only frontal region which did not show any sensitivity to the level of associative chunk strength on either of the test days (i.e., day 1 and day 8). This lends further support to the suggestion that the left inferior frontal region (BA 45) has a specific role in the processing structural regularities, while the right inferior frontal gyrus might be involved in more generic error detection processes (cf., Indefrey, Hagoort, Herzog, Seitz, & Brown, 2001).

Recurrent corticostriatal networks

The present results show that grammaticality endorsement (i.e., G vs. NG) correlates with caudate nucleus activity while syntactic violations (NG vs. G) correlate with the left inferior frontal cortex activation. This might result from integration (i.e., parsing) difficulties during processing of NG strings. These findings are in line with a procedural mechanisms for recursive integration of structured representations and it might be the case that the involvement of the basal ganglia reflect automatic aspect of the integration and the processing syntactic form, perhaps in interaction with the left inferior frontal region. For example, it has been suggested that neural systems supporting procedural learning and that are important for the on-line governing of the parsing process depend on recurrent networks implemented in corticostriatal loops (cf. e.g., Luciana, 2003; Nelson & Webb, 2003). Taken together, it might be suggested that the processing of inherently meaningless artificial grammar strings is dependent on the neural architecture for procedural learning, as well as regions implicated in general integrative processes in the analysis of linguistic form (left BA 44/45), and when aspects of this integration process becomes automatic, also on the head of the caudate nucleus.

Grammar learning

As previously noted in the introduction, 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 FSA. The FSA 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. However, it should be noted that the FSA behaves as a Turing machine as long as the memory limitations are not encountered (Petersson, Grenholm, & Forkstam, 2005). 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 FSA, although a context-sensitive or any other suitable formalism might be used as long as the finite memory organization is appropriately handled (Petersson, 2005b; Petersson et al., 2004).

Prefrontal function and 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, 2003; Baddeley, Gathercole, & Papagano, 1998) processing and integration of structured information ('manipulation' and 'selection'), as well as monitoring and inhibition (Fuster, 1997; Mesulam, 1998, 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, 2005b; Petersson et al., 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 $s_l = s_i$. We note 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).

In summary, the picture just outlined provides an alternative view on AGL 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 a unification space (e.g., working memory) during parsing. The latter process is dependent on general integrative mechanisms in the left inferior frontal cortex, and when automaticity has developed, some aspects of this process appears to engage the head of the caudate nucleus.

References

Baddeley, A. (2003). Working memory: looking back and looking forward. *Nat. Rev. Neurosci., 4*, 829-839.

Baddeley, A., Gathercole, S., & Papagano, C. (1998). The phonological loop as a language learning device. *Psychol. Rev., 105*, 158-173.

Chomsky, N. (1986). *Knowledge of Language*. New York: Praeger.

Chomsky, N. (1995). *The Minimalist Program*. Cambridge, MA: MIT Press.

Davis, M. D., Sigal, R., & Weyuker, E. J. (1994). *Computability, Complexity, and Languages: Fundamentals of Theoretical Computer Science* (2 ed.). San Diego, CA: Academic Press.

Ellefson, M. R., & Christiansen, M. H. (2000). *Subjacency constraints without universal grammar: evidence from artificial language learning and connectionist modeling*. Paper presented at the 22nd annual conference of the Cognitive Science Society.

Forkstam, C., & Petersson, K. M. (2005). Towards an explicit account of implicit learning. *Accepted for publication in Current Opinion in Neurology*.

Friederici, A. D., Steinhauer, K., & Pfeifer, E. (2002). Brain signatures of artificial language processing: Evidence challenging the critical period hypothesis. *Proc. Natl. Acad. Sci. USA, 99*, 529-534.

Fuster, J. M. (1997). *The Prefrontal Cortex: Anatomy, Physiology, and Neuropsychology of the Frontal Lobe* (3 ed.). New York: Lippincott-Raven.

Gomez, R. L., & Gerken, L. (1999). Artificial grammar learning by 1-year-olds leads to specific and abstract knowledge. *Cognition, 70*, 109-135.

Gomez, R. L., & Gerken, L. (2000). Infant artificial language learning and language acquisition. *Trends Cogn. Sci., 4*, 178-186.

Indefrey, P., Hagoort, P., Herzog, H., Seitz, R. J., & Brown, C. M. (2001). Syntactic processing in left prefrontal cortex is independent of lexical meaning. *NeuroImage, 14*, 546-555.

Jackendoff, R. (2002). *Foundations of Language: Brain, Meaning, Grammar, Evolution*. Oxford, UK: Oxford University Press.

Joshi, A. K., & Schabes, Y. (1997). *Tree-adjoining grammars.* In A. Salomaa (Ed.), Handbook of Formal Languages (Vol. 3: Beyond words). Berlin: Springer Verlag.

Knowlton, B. J., & Squire, L. R. (1996). Artificial grammar learning depends on implicit acquisition of both abstract and exemplar-specific information. *J. Exp. Psychol. Learn. Mem. Cogn., 22*, 169-181.

Lieberman, M. D., Chang, G. Y., Chiao, J., Bookheimer, S. Y., & Knowlton, B. J. (2004). An event-related fMRI study of artificial grammar learning in a balanced chunk strength design. *J. Cogn. Neurosci., 16*, 427-438.

Luciana, M. (2003). The neural and functional development of human prefrontal cortex. In M. de Haan & M. H. Johnson (Eds.), *The Cognitive Neuroscience of Development* (pp. 157-179). New York: Psychology press.

Marcus, G. F., Vijayan, S., Bandi Rao, S., & Vishton, P. M. (1999). Rule learning by seven-month-old infants. *Science, 283*(5398), 77-80.

Mesulam, M. M. (1998). From sensation to cognition. *Brain, 121*, 1013-1052.

Mesulam, M. M. (Ed.). (2002). *The Human Frontal Lobes: Transcending the default mode through contingent encoding*. Oxford, UK: Oxford University Press.

Meulemans, T., & Van der Linden, M. (1997). Associative chunk strength in artificial grammar learning. *J. Exp. Psychol. Learn. Mem. Cogn., 23*, 1007-1028.

Nelson, C. A., & Webb, S. J. (2003). A cognitive neuroscience perspective on early memory development. In M. de Haan & M. H. Johnson (Eds.), *The Cognitive Neuroscience of Development* (pp. 99-125). New York: Psychology press.

Opitz, B., & Friederici, A. D. (2003). Interactions of the hippocampal system and the prefrontal cortex in learning language-like rules. *NeuroImage, 19*, 1730-1737.

Perruchet, P., & Pacteau, C. (1991). Implicit acquisition of abstract knowledge about artificial grammar: Some methodological and conceptual issues. *J. Exp. Psychol. Gen., 120*, 112-116.

Petersson, K. M. (2005a). *Learning and Memory in the Human Brain*. Stockholm, Sweden: Karolinska University Press.

Petersson, K. M. (2005b). On the relevence of the neurobiological analogue of the finite state machine. *Neurocomputing, 65-66*, 825-832.

Petersson, K. M., Forkstam, C., & Ingvar, M. (2004). Artificial syntactic violations activate Broca's region. *Cognitive science, 28*, 383-407.

Petersson, K. M., Grenholm, P., & Forkstam, C. (2005). Artificial grammar learning and neural networks. *Accepted for publication in the Proceeding of the Cognitive Science Society*.

Poletiek, F. H. (2002). Implicit learning of a recursive rule in an artificial grammar. *Acta Psychol. (Amst.), 111*, 323-335.

Reber, A. S. (1967). Implicit learning of artificial grammars. *J. Verb. Learn. Verb. Behav., 5*, 855-863.

Reber, A. S. (1993). *Implicit Learning and Tacit Knowledge : An Essay on the Cognitive Unconscious*. New York: Oxford Univ. Press.

Reber, A. S., & Allen, R. (1978). Analogy and abstraction strategies in synthetic grammar learning: A functional interpretation. *Cognition, 6*, 189-221.

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science, 274*, 1926-1928.

Seger, C. A., Prabhakaran, V., Poldrack, R. A., & Gabrieli, J. D. (2000). Neural activity differs between explicit and implicit learning of artificial grammar strings: An fMRI study. *Psychobiology, 28*, 283-292.

Skosnik, P. D., Mirza, F., Gitelman, D. R., Parrish, T. B., Mesulam, M. M., & Reber, P. J. (2002). Neural correlates of artificial grammar learning. *NeuroImage, 17*, 1306-1314.

Stadler, M. A., & Frensch, P. A. (Eds.). (1998). *Handbook of Implicit Learning*. London: SAGE.

Strange, B. A., Henson, R. N. A., Friston, K. J., & Dolan, R. J. (2001). Anterior prefrontal cortex mediates rule learning in humans. *Cerebral Cortex, 11*, 1040-1046.

Vokey, J. R., & Brooks, L. R. (1992). Salience of item knowledge in learning artificial grammar. *J. Exp. Psychol. Learn. Mem. Cogn. 18*, 328-344.

Worsley, K., Marrett, S., Neelin, P., Vandal, A. C., Friston, K. J., & Evans, A. (1996). A unified statistical approach for determining significant signals in images of cerebral activation. *Hum. Brain Map., 4*, 58-73.

Vosse, T., & Kempen, G. (2000). Syntactic structure assembly in human parsing: a computational model based on competitive inhibition and a lexicalist grammar. *Cognition, 75*, 105-143.