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Concurrence of rule- and similarity-based mechanisms in artificial grammar learning

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ABSTRACT

A current theoretical debate regards whether rule-based or similarity-based learning prevails during artificial grammar learning (AGL). Although the majority of findings are consistent with a similarity-based account of AGL it has been argued that these results were obtained only after limited exposure to study exemplars, and performance on subsequent grammaticality judgment tests has often been barely above chance level. In three experiments the conditions were investigated under which rule- and similarity-based learning could be applied. Participants were exposed to exemplars of an artificial grammar under different (implicit and explicit) learning instructions. The analysis of receiver operating characteristics (ROC) during a final grammaticality judgment test revealed that explicit but not implicit learning led to rule knowledge. It also demonstrated that this knowledge base is built up gradually while similarity knowledge governed the initial state of learning. Together these results indicate that rule- and similarity-based mechanisms concur during AGL. Moreover, it could be speculated that two different rule processes might operate in parallel; bottom-up learning via gradual rule extraction and top-down learning via rule testing. Crucially, the latter is facilitated by performance feedback that encourages explicit hypothesis testing.

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1. Introduction

The question, what do people learn when they are exposed to highly structured complex stimuli, initially posed over 40 years ago (Reber, 1967), is still intensely debated. Of the major concern for cognitive psychology is the question whether people are able to learn abstract rules or whether they base their judgments about novel instances on the similarity of these instance to some previously-encountered cases. The rule-based vs. similarity-based debate has previously been considered in many contexts: in theories of reasoning (Ross, 1989; Ross & Kennedy, 1990; Sun, 1995), in instance-based models of implicit learning (Berry & Broadbent, 1984; Redington & Chater, 2002; Vokey & Brooks, 1992), or in the domain of category learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & O'Brien, 2005; Erickson & Kruschke, 1998; Maddox, Ashby, & Bohil, 2003). For example, within the domain of category learning there is considerable empirical evidence that rule-based and similarity-based mechanisms both contribute to learning (e.g., Ashby & Maddox, 2005). One paradigm that is particularly well suited to investigate this question is artificial grammar learning (AGL). This is because AGL paradigms afford the differential assessment of learnable structures (Fitch & Hauser, 2004; Lai & Poletiek, 2011; Poletiek, 2011; Vries, de Vries, Monaghan, Knecht, & Zwitserlood, 2008), and the properties which facilitate the learning of those structures (Endress, Scholl, & Mehler, 2005; Gómez & Gerken, 2000; Marcus, Vijayan, Rao, & Vishton, 1999). A typical AGL experiment contains two phases. In the exposure or training phase participants are presented with some letter strings. Unbeknown to participants, these letter strings, also called grammatical items, are generated by a finite state grammar. Subsequent to the exposure phase participants are presented with novel items comprising either grammatical or non-grammatical sequences. Their task is to identify those letter strings that violate the finite state grammar. A series of studies has shown that participants perform this task above chance (e.g., Dienes, Broadbent, & Berry, 1991; Kinder & Assmann, 2000; Lotz & Kinder, 2006; Mathews et al., 1989; Pothos & Bailey, 2000; Reber, 1967, 1976, 1989). Two major competing theories have been proposed to account for this result (see Pothos, 2005, 2007 for reviews). Both are highly plausible and supported by substantive empirical evidence. One view proposes that participants perform this task by judging the similarity of the novel stimuli in reference to the stimuli, or at least fragments of these stimuli, memorised in the exposure phase (Brooks & Vokey, 1991; Kinder & Assmann, 2000; Perruchet & Rey, 2005; Vokey & Brooks, 1994).

An alternative view suggests that rules underlying the construction of these stimuli are learned (Mathews et al., 1989; Reber, 1989). Rule-based accounts are highly attractive because, for example, one easily reckons why the number 1356 is even or whether a geometric shape represents a triangle. Further phenomenological evidence for the existence of rules in cognition has been previously demonstrated (Smith, Langston, & Nisbett, 1992). Applied to artificial grammar learning, rules can be understood as a computational construct of mental representations capturing abstract statistical regularities of several grammatical stimuli (Opitz, 2010; Sun, 1995) or as mental operations allowing the characterisation of a stimulus according to a minimal number of features (Pothos, 2007). Irrespective of the exact understanding of rules, both views share a number of assumptions about rules (see Hahn & Chater, 1998 for a detailed discussion of these assumptions). Among them, rules are considered to be *compositional* so that complex rules can be constructed from simple rules. For example, two rules 'Valid strings of the artificial grammar start with T' and 'Valid strings end with R' can be combined into the compositional rule 'Valid strings start with T and end with R'. Furthermore, rules imply abstract representations to allow for generalisation to a sufficiently large number of instances. Rules also represent an exact and rigorous description of the relevant abstract knowledge. The downside of this property is the inflexibility and limited scope of rule judgments: for the rule to apply, the preconditions of the rule must typically be matched in an all-or-none fashion (Hahn & Chater, 1998). Critically, if not all preconditions are known the missing ones must be assumed to match. For instance, to classify an animal that has four legs and is furry as a dog one has to assume that, among other features, it barks, as well. If that assumption is not made, than the rule does not apply to that particular item. Note that, although not knowing all preconditions causes some uncertainty in the applicability of a rule, the actual application of this rule implies that all preconditions were (assumed to be) met. There is no intermediate state that allows for some flexibility in the application of rules.

In contrast, the strength of similarity processes is clearly their flexibility. A similarity judgment for any two letter strings or a string and a mental representation will always be possible. The underlying comparison process does not require any abstraction and involves as many as possible (if not all) properties of the stimulus. The more properties match, the greater the similarity between a novel and the memorised letter string. Moreover, it does not matter for similarity to be applied whether any particular property is not matched.

The knowledge representation acquired during AGL was usually inferred from participants' performance in a grammaticality judgment after some learning has occurred during the exposure phase. In his seminal work Reber (1967, 1969) has argued that at least partial abstract knowledge about the rule underlying the artificial grammar has been acquired. As first evidence for this claim he considered the original finding that almost 80% of the grammatical strings were endorsed as grammatical but only 22% of the non-grammatical strings (Reber, 1967). Further evidence for abstract rule knowledge comes from later work demonstrating participants' ability to transfer their knowledge to strings composed of novel letters (Reber, 1969, 1989). In such transfer experiments participants were trained with one letter set (e.g., T, V, P, S, and X) but were tested with novel letters (e.g., R, C, F, G, and L). Despite performance in such transfer experiments being worse than in experiments requiring no transfer it is still above chance indicating that participants must have acquired some abstract knowledge about the underlying grammatical rules (Gómez & Schvaneveldt, 1994; Mathews et al., 1989; Reber, 1969; Tunney & Altmann, 1999). This abstract knowledge is at least partly independent of the surface realisation of the grammar, i.e. independent of the letter set used.

The evidence for rule-based learning was subsequently criticised on different grounds. It has been argued, for instance, that the difference between grammatical and non-grammatical strings often covaries with the similarity of the items used for learning and subsequent testing. Grammatical test items tend to be more similar to the learning items presented in the exposure phase compared to non-grammatical test items. Several attempts have been made to equalise grammatical and non-grammatical strings with respect to several stimulus parameters that might influence similarity-based judgments (Jamieson & Mewhort, 2009; Kinder & Assmann, 2000; Kinder & Lotz, 2009; Pothos, 2005; Pothos & Bailey, 2000; Tunney, 2010; Vokey & Brooks, 1992). These parameters could be roughly divided into two classes that affect either the global similarity to all sequences used for learning and testing or the similarity to a subset of sequences. One common measure for this latter specific similarity is the so-called *edit distance* that indicates the number of transformations (omission, insertion, and exchange of letters) required to convert one letter string into another (Vokey & Brooks, 1992, 1994). Accepting only those test items as similar that could be produced by a single transformation of at least one learning item (edit distance one) it was demonstrated that similar test items were endorsed more often as grammatical as compared to dissimilar items, irrespective of the actual grammaticality status. This specific similarity has also been involved in knowledge transfer to novel vocabulary (Brooks, 1978; Brooks & Vokey, 1991; Vokey & Higham, 2005). It was shown that specific similarity contributed to overall performance irrespective of the surface characteristics of the test items (Vokey & Higham, 2005). Interestingly, this transfer is much higher for strings containing repeating elements than for strings without such elements (Gómez, Gerken, & Schvaneveldt, 2000; Tunney & Altmann, 2001; Vokey & Higham, 2005) and even more pronounced for repetitions at salient positions (at the beginning or the end of a string) as compared to less salient positions in the middle of the string (Endress et al., 2005). This dependency on perceptual characteristics was taken as evidence against rule-based learning as originally formulated by Reber (1989) which would predict similar transfer for all positions within the letter string.

As a common alternative to specific similarity, it has been argued that the key factor determining performance in AG is global similarity of a particular test item to all learning strings (Jamieson & Mewhort, 2009; Pothos, 2005; Pothos & Bailey, 2000). Pothos and Bailey (2000) identified global similarity on the basis of their participants' subjective evaluation and reported a significant influence of this kind of similarity on grammaticality judgments. Yet others have argued that not the entire test string is compared to the mental representation of all learning items, but that only particular string fragments (chunks comprised of bigrams, trigrams, etc.) are used to judge novel test string as grammatical or non-grammatical (Knowlton & Squire, 1994, 1996; Perruchet & Pacteau, 1990). The recognition of chunks is sufficient to explain performance in the AGL task. Although a similar performance

was achieved after exposure either to bigrams or to full strings during learning, participants in the former condition were not able to identify grammatical chunks in positions that render the string non-grammatical (Perruchet & Pacteau, 1990). It was concluded that the similarity of particular bigrams of the test item to all learned bigrams was utilised for the grammaticality judgment during test. Capitalising on these initial findings Knowlton and Squire (1994, 1996) have shown that test items were endorsed more often as grammatical when their chunk strength, i.e. the number of chunks frequently occurring during the exposure phase, is high. Additionally, it was argued that the number of letters forming a particular chunk increases during learning, and that fewer chunks increase chunk strength and therefore the similarity of the test string to all learned strings. Importantly, so-called anchor chunks, i.e. very salient chunks at the beginning or the end of a string, will contribute more to the overall performance than less salient chunks in the middle of a string (Endress et al., 2005; Meulemans & van der Linden, 1997).

Crucially, the effect of chunks has been shown to eliminate the effect of specific similarity when similar and dissimilar items were balanced for chunk strength (Knowlton & Squire, 1994). In apparent contrast, other studies reported the opposite; effects of specific similarity when test strings were balanced for chunk strength (e.g., Meulemans & van der Linden, 1997). Further studies tried to disentangle the influence of specific and global similarity measures on learning using a regression approach (Kinder & Assmann, 2000; Lotz, Kinder, & Lachnit, 2009; Pothos & Bailey, 2000). However, these different approaches to measure similarity led to heterogeneous results. While Pothos and Bailey (2000) reported a prevailing influence of subjective similarity and only a minor effect of chunks, other studies found chunks to have a major influence on grammaticality judgments (Kinder & Assmann, 2000; Lotz et al., 2009). This influence of chunks is reduced, however, when the occurrence of infrequent letters was taken into account (Kinder & Assmann, 2000). This might suggest that the participants in this study established a rule that the absence or presence of certain infrequent, and therefore salient, letters is indicative of the grammatical status of a particular letter string.

Despite this numerous evidence for similarity-based, it has been argued that the majority of studies have involved only limited exposure to study exemplars, and performance on subsequent grammaticality judgment tests has often been just above chance level (Domangue, Mathews, Sun, Roussel, & Guidry, 2004; Sallas, Mathews, Lane, & Sun, 2007). This argument rests on previous findings demonstrating that similarity-based learning is fast and relatively effortless but less accurate while rule-based processing is laborious and slow but yields high levels of grammatical knowledge (Domangue et al., 2004). Similarly, it was reported that rule-knowledge of an artificial language, as measured by the performance after changing the underlying rule without changing the vocabulary, gradually developed during the course of learning while similarity knowledge, i.e., after changing the vocabulary without changing the grammatical rules, affected the initial phase of learning only (Opitz & Friederici, 2004). Hence, rule knowledge emerges over time and requires a certain degree of exposure to the grammar. The emergence of rule knowledge might be indicated by fast and accurate task performance as perfect knowledge of the underlying grammatical rules would lead to perfect discrimination ability. In line with this argument, AGL studies on exposure length reported an increase in rule-knowledge and a decrease in similarity-knowledge over time (Fletcher, Büchel, Josephs, Friston, & Dolan, 1999).

Thus, the aim of the present study is to investigate the contribution of rule-based and similarity-based learning under conditions that foster performance in the grammatical judgment task by employing immediate performance feedback during learning. To overcome the controversies around different measures of similarity the analysis of receiver-operating characteristics (ROC) will be employed (Kinder & Assmann, 2000; Lotz & Kinder, 2006) to capture classification performance as a measure of discrimination accuracy. This analysis has emerged from signal detection theory and describes the ratio of the true positive rate (i.e. the sensitivity), and false positive rate ($1 - \text{specificity}$). In case of AGL, participants are asked to classify test items according to their conformity with some underlying rules. The respective classification performance, i.e. true positive rate (endorsing grammatical stimuli in fact as grammatical) vs. false positive rate (incorrectly endorsing non-grammatical stimuli) is plotted as the confidence (ranging from, 'surely grammatical' to, 'surely non-grammatical') changes.

The shape of the ROC can then be fitted by theoretical curves that are derived from the characteristics of similarity and rule knowledge (see [Supplementary material](#) for details of this derivation). One advantage of the ROC approach over traditional grammaticality judgment tasks is the idea that any similarity judgment, irrespective of whether it is based on measures of specific or global similarity, is made on a continuous dimension (i.e., more or less similar, cf. [Pothos, 2007](#); [Servan-Schreiber & Anderson, 1990](#)). The signal detection theory assumes that the similarity varies in accordance with a normal distribution ([Green & Swets, 1966](#)). The most common variant of the signal detection theory, the so-called equal-variance signal detection model, further assumes two different distributions for grammatical and non-grammatical sentences having the same variance. Whether or not an item is called grammatical during the test depends on whether its similarity exceeds or falls below the response criterion at a given confidence level. The shape of the resulting model function will be a perfectly symmetrical curvilinear ROC. When transformed into *z*-space, this model will produce a linear *z*-ROC with a slope of 1 ([Lotz & Kinder, 2006](#); [Yonelinas, 1994](#)).

Another model, which assumes differences in the variances of the distributions of grammatical and non-grammatical items is called unequal-variance signal detection model (UVSD). Because grammatical items are encountered during the initial phase of a typical AGL paradigm the variance of the grammatical items' similarity distribution is assumed to be greater than the distribution of the non-grammatical items and the resulting ROC will be curvilinear but asymmetric and *z*-ROC is linear with a slope equal to the ratio of the standard deviations of the non-grammatical and grammatical item distributions typically being less than one.

A third model acknowledges the contribution of rule knowledge to the grammaticality judgment. As previously discussed, rule knowledge can be described in terms of an all-or-none process, i.e. a test string either adheres to the rules of the artificial grammar somebody has learned or it does not ([Dienes & Berry, 1997](#); [Hahn & Chater, 1998](#)). This property of rule-based processes can be mathematically described by a high-threshold model. This model assumes distinguishable classes of sentences with grammatical sentences falling above the threshold and non-grammatical items falling below. That is, if test items match all previously learned rules the threshold is exceeded and the item will be endorsed as grammatical. Such a threshold process will generate a strictly linear ROC in probability space and a slightly U-shaped *z*-ROC with a slope that differs from 1. If both, rule knowledge and similarity knowledge were applied in AGL the resulting ROC is somewhere in between the two extreme positions described above, with the curvature reflecting the amount of similarity knowledge. The parameter estimates of the best fitting model ROC can then be taken to indicate the proportion of rule-based and similarity-based processes in a particular experiment. It is predicted that higher estimates of rule-based learning will (a) be observed after explicit learning employing immediate performance feedback as compared to typical memorisation instruction and will (b) gradually develop during the course of learning.

2. Experiment 1

This experiment tested the first hypothesis by comparing two groups of participants. While one group received working memory instructions as originally employed by [Reber \(1967\)](#) and subsequently used in a large variety of studies the other group was informed that a rule system was underlying the sentences prior to the experiment and that they had to learn these rules using the feedback provided.

2.1. Participants

The participants were 43 students from Saarland University, Saarbrücken who received monetary compensation (8€ per hour) or course credits for their participation. They all were monolingual, native speakers of German. The participants (22 male) were from 19 to 29 years old ($M = 23.1$ years), had normal or corrected-to-normal vision and were without any history of neurological or psychiatric disorder. The participants were divided into two groups performing either an explicit ($n = 23$) or an implicit ($n = 20$) version of the task.

2.2. Stimuli

The stimulus material was formed according to the artificial language BROCANTO (Friederici, Steinhauer, & Pfeifer, 2002; Opitz & Friederici, 2003, see Fig. 1). The vocabulary comprised fourteen words from five different word categories: nouns (N), verbs (v), determiners (D, d), adjectives (M) and adverbs (m). Word categories contained two to four members and were identifiable by particular vowels (e.g., u, o = noun or e, i = verb). Each sentence of the artificial language built from this vocabulary, contained three to eight words and represented a subject-verb-[object] structure. The subject and the object of a sentence was a noun phrase (NP) composed of a determiner (D, d), an optional adjective (M), and a noun (N). The verb phrase (VP) consisted of a verb (v) and an optional adverb (m). A total of 200 sentences were formulated according to these rules. Another 200 contained a severe syntactic violation. Three types of violations were constructed covering a wide range of possible violations. These include violations of the phrase structure (i.e., an NP was presented instead of VP), violations of the determiner–adjective–noun agreement, and word class repetitions (see also Opitz & Friederici, 2003). In order to control for global and specific similarity of grammatical and non-grammatical sentences all words and possible combinations of words (bigrams, e.g., a verb followed by an adverb and trigrams, e.g., a determiner followed by an adjective followed by a noun) within phrases occurred equally often in grammatical and non-grammatical sentences (see Supplement 2 for a list of all stimuli used).

2.3. Procedure

All participants were exposed to the same sentences generated by BROCANTO. One group of participants received working memory instructions (implicit learning group). The other group was

Fig. 1. Schematic representation of the artificial grammar BROCANTO used (A) in Experiments 1 and 2 and (B) in Experiment 3. Nodes specify word classes (N, noun; v, verb; M, noun modifier (adjective); (m), optional verb modifier (adverb); d and D, determiner; c, complementizer), while arrows denote valid transitions between nodes. A correct sentence is formed by a transition from beginning ([) to end (]). Examples of correct and incorrect sentences are given in (C).

informed that a rule system was underlying the sentences prior to the experiment and that they had to learn these rules (explicit learning group).

Participants of the implicit learning group were told that they were taking part in a short-term memory experiment and that they had to remember a consecution of pseudowords. The 100 grammatical training items were presented one at a time on the computer screen for 7 s each. After an item had disappeared, the participant had to repeat the entire word sequence in the correct order aloud. Participants' responses were documented by the experimenter. If the participant did not correctly reproduce the sequence, it was shown again until it was reproduced without any mistakes or a maximum of three repetitions had been reached. This procedure resulted on average in two repetitions of a training sentence.

The training phase for the explicit learning group was similarly constructed to previous studies examining artificial language systems (Opitz & Friederici, 2003, 2007). It comprised alternating learning and test blocks presented in a fixed order. A brief instruction began each block. During learning blocks, participants viewed 20 correct sentences for 7 s each on a computer monitor and were instructed to extract the underlying grammatical rules. During test blocks, participants were presented with 20 new sentences (7 s each) that were either grammatical/correct (half of the sentences) or non-grammatical/incorrect. The participants' task was a grammaticality judgment on each presented sentence. Visual feedback in terms of the written words "richtig" ("correct", written in green) or "falsch" ("incorrect", written in red) was given for the duration of 500 ms after each response. The 100 training sentences were presented twice in different order to equate the total number of occurrences of a particular correct sentence between the two groups.

After training both groups were admitted to a final test phase. Here, the participants of the implicit learning group were informed for the first time that the sequences they had just seen followed a complex set of rules. All participants were asked to judge the correctness of a new set of 200 sentences according to these rules. Each sentence was displayed for 7 s followed by a fixation cross shown for 1 s. Grammaticality judgments were given on a 6 point rating scale allowing the participants to additionally state the confidence of their judgments (ranging from 1, "surely grammatically correct" to 3, "somewhat grammatically correct" for the supposedly grammatical sentences and from 4, "somewhat grammatically incorrect" to 6, "surely grammatically incorrect" for the supposedly non-grammatical sentences). In contrast to the training phase no feedback was provided in order to prevent further learning.

2.4. Data analysis

To compare our results with the results of previous studies (e.g., Kinder & Assmann, 2000; Knowlton & Squire, 1994), we counted responses from 1 to 3 as "grammatical" judgments and responses from 4 to 6 as "non-grammatical" judgments. Mean endorsement rates (i.e., mean proportion of "grammatical" responses) for grammatical and the three types of non-grammatical sentences were subjected to a repeated-measure ANOVA with the factor sentence type (grammatical vs. three types of non-grammatical sentences) and the between-subject factor group (implicit vs. explicit learning group). Subsidiary ANOVAs were performed to compare the performance for the three types of non-grammatical sentences.

For the analysis of the ROC true positives were defined as the correct identification of grammatical sentences (i.e., "gr" | gr; "grammatical" answer to a grammatical sentence) and false positives as a "grammatical" answer to grammatically incorrect, i.e. non-grammatical sentences ("gr" | non-gr). Empirical ROC points were then constructed by cumulating the mean true and false positive rates separately across levels of confidence. Thus, the first point on the ROC represents the performance for the first confidence level, i.e. surely correct/grammatical responses. This procedure was continued for each successive level of confidence ending with the surely incorrect/non-grammatical responses. For comparison with the previously reported results (e.g., Kinder & Assmann, 2000) the average ROCs are plotted in probability space and z-space. To test our specific predictions regarding the contributions of similarity and rule knowledge to AGL two analyses were carried out. Firstly, to find out whether z-ROCs had a slope different from 1 and/or whether they had a significant quadratic component indicating nonlinearity, a regression analysis including a linear and quadratic term was

computed for every participant. The coefficients obtained in these analyses were subjected to one-sample *t*-tests.

To test our specific predictions regarding the contributions of similarity and rule knowledge to AGL several theoretically derived models were fitted to the empirically obtained ROC points (see [Supplementary information](#) for further details on the different models). A basic assumption inherent to all models is that rule and similarity knowledge remain constant across different levels of confidence and only the response criterion varies. All calculations were performed using a maximum likelihood estimation procedure described by [Ogilvie and Creelman \(1968\)](#) with the Excel solver. This procedure adjusts the estimates for rule and similarity knowledge (and the response criteria) by minimising the difference between the log-likelihood of the fitted model and the data. The resulting G^2 statistic is a likelihood-ratio test statistic expressing the deviance of the fitted model from the observed data. Thus, small values of G^2 indicate better model fits. Because the estimated values of the criterion parameters are not of theoretical interest and do not determine the shape of the ROC in any way, only the values of the two defining parameters (R and/or $S|c_i = 0$) of each model are reported.

2.5. Results

For both groups, the grammatical test sentences were endorsed more often than the three types of non-grammatical sentences ([Table 1](#)). This was revealed by a significant main effect of sentence type (grammatical vs. three non-grammatical: $F_{3,123} = 34.94, p < .001, \eta_p^2 = .460$). The significant sentence type by group interaction ($F_{2,123} = 9.01, p < .001, \eta_p^2 = .180$) indicated that the explicit group outperformed the implicit group. The explicit group endorsed more of the grammatical sentences than of the non-grammatical sentences ($F_{1,22} = 210.07, p < .001, \eta_p^2 = .905$). The implicit learning group also performed above chance level as indicated by higher endorsement rate for grammatical as compared to non-grammatical sentences ($F_{1,19} = 22.89, p < .05, \eta_p^2 = .564$).

A subsidiary ANOVA comparing the endorsement rates for the three violation types separately for the two groups indicated a main effect of violation type ($F_{2,44} = 9.33, p < .005, \eta_p^2 = .298$) for the explicit learning group while for the implicit learning group the endorsement rates for the three violation types did not differ significantly from each other ($F_{2,38} = 1.73, p = .197, \eta_p^2 = .083$) indicating that this latter group did not learn any particular rule.

To further evaluate the response pattern in the explicit learning group in more detail a two-step clustering analysis was performed based on Akaike Information Criterion. This analysis indicated three sub-groups differing in their response pattern for the three violation types ([Table 2](#)). As indicated by high endorsement rates for grammatical sentences and low endorsement rates for all three types of

Table 1
Mean endorsement rates ($\pm$ SEM) for grammatical sentences and the three types of grammatical violations.

Group	Grammatical sentences	Agreement violations	Word class repetitions	Phrase structure violations
Implicit learning group	.706 (.026)	.612 (.038)	.515 (.049)	.533 (.048)
Explicit learning group	.707 (.028)	.422 (.064)	.113 (.022)	.167 (.052)

Table 2
Mean endorsement rates ($\pm$ SEM) for grammatical sentences and the three types of grammatical violations for the three groups of participants from the explicit learning group based on a two-step cluster analysis.

Group	Grammatical sentences	Agreement violations	Word class repetitions	Phrase structure violations
Subgroup 1 ($N = 12$)	.685 (.042)	.188 (.034)	.094 (.028)	.052 (.010)
Subgroup 2 ($N = 7$)	.773 (.046)	.743 (.047)	.127 (.049)	.077 (.022)
Subgroup 3 ($N = 4$)	.656 (.045)	.105 (.039)	.145 (.052)	.672 (.096)

Fig. 2. Receiver-operating characteristics for the explicit learning group (A) and the implicit learning group (B). ROC in probability space are plotted in the left column, ROC in z-space are in the right column. Triangles indicate empirical data; lines indicate the model generated ROC: black solid line – hybrid model; dotted line – rule only (high threshold) model; dashed line – similarity only (signal detection) model; solid grey line – similarity only (UVSD) model.

non-grammatical sentences the largest group of participants ($N = 12$) learnt the complete set of the grammatical rules. All other participants learnt only a subset of the grammatical rules allowing them to correctly identify either phrase structure violations ($N = 7$) or agreement violations ($N = 4$). The low endorsement rates for word class repetitions across all sub-groups suggest that the rule underlying this specific type of violation was easiest to learn.

Receiver operating characteristics (ROC), displaying true positive/false positive-ratios at different confidence levels which ranged from 1 (surely grammatical) to 6 (surely non-grammatical), were obtained from all participants. For the explicit learning group the measured ROC points in probability space (Fig. 2A, left) formed an asymmetrical curve and the ROC in z-space (Fig. 2A, right) appears to be curvilinear with a slope less than 1. This indicates the involvement of both rule- and similarity-based mechanisms in learning the artificial language. In contrast, for the implicit learning group the shape of the ROC in probability space was rather symmetrical (Fig. 2B, left) and the ROC in z-space followed a linear function (Fig. 2B, right), suggestive for a sole contribution of similarity-based mechanisms.

The shape of the z-ROCs was then examined to determine whether they were linear or curvilinear. A regression analysis including a linear and quadratic term was computed for every participant with the coefficients obtained in these analyses subjected to one-sample t -tests. For the explicit learning group¹ the regression revealed that the z-ROC had a marginally significant quadratic term ($t_{21} = -1.95, p < .065$) and the linear term differed significantly from 1 ($t_{21} = 4.02, p < .001$). Hence, the z-ROC for the explicit learning group is curvilinear rather than linear indicating the contribution of a threshold, i.e., rule-based mechanism. For the implicit learning group neither the quadratic term did

¹ For this analysis one participant of the explicit learning group had to be excluded because this participant had an insufficient number of low confidence responses prohibiting a reliable calculation of this participant's z-ROC.

differ from zero ($t_{19} = .46, p < .65$) nor did the linear term differ significantly from 1 ($t_{19} = 1.40, p < .18$). This indicates that the shape of the z-ROC for the implicit learning group is in agreement with the sole contribution of similarity-based mechanisms.

To corroborate these findings in the next step the four theoretical models, i.e. the high-threshold (rule only) model, the equal- and unequal-variance signal detection (similarity only) models, and the hybrid model including both processes were fitted to the empirically obtained ROC points in probability space. These models were used to derive parameter estimates for rule [R] and similarity [S] from both cumulated and individual ROC curves. Model-generated curves for cumulated ROC points are shown as lines in Fig. 2A. As apparent from the figure, the hybrid model seems to best account for the data of the explicit learning group while a similarity only (signal detection) model seems to be sufficient for the implicit learning group. Minimising the G^2 for the difference between observed and expected values on the cumulated ROCs revealed the parameter estimates shown in Table 3. For the explicit learning group all model fits differed not significantly from the empirical data as indicated by non-significant G^2 -value.

Nevertheless, across all participants the difference between empirical data and model fit was minimised in the hybrid model. The goodness of fit measures revealed a significant improvement of the hybrid model fit as compared to similarity only model ($G^2_1 = 5.58; p < .05$) and the rule only model ($G^2_5 = 13.42; p < .05$). In contrast, for the implicit learning group the rule only model differed significantly from the empirical data (see Table 3) while both similarity only models and the hybrid model provided identical fits. As the hybrid model provided the best fit, all further analyses were based on the hybrid model. To test the statistical significance of these cumulative model fits, the hybrid model was fitted to individual ROCs in order to obtain rule and similarity parameters for every participant. The mean estimates for R and S derived from individual ROCs are presented in Fig. 3 and were of comparable magnitude as the parameter values derived from cumulated ROCs. These estimates were subjected to an

Table 3
Rule [R] and similarity [S] parameter estimates and G^2 goodness-of-fit statistics for the four models fit to the cumulative ROC data.

Model fit	R	S	σ_{gr}	G^2	d.f.	p
<i>Explicit learning group</i>						
Hybrid model	.41	.47	1	1.66	3	.65
Rule only	.61	–	–	15.08	8	.06
Similarity only	–	.69	1	7.24	4	.12
UVSD	–	.71	1.33	1.00	5	.96
<i>Implicit learning group</i>						
Hybrid model	–	.71	1	.32	3	.99
Rule only	.61	–	–	46.18	8	.01
Similarity only	–	.71	1	.32	4	.99
UVSD	–	.70	0.96	1.19	5	.95

Fig. 3. Parameter estimates for individual ROCs for Experiment 1. Parameter estimates were derived using the formal hybrid model. Error bars represent standard errors of the means.

analysis of variance which revealed a significant main effect of parameter estimate (rule vs. similarity: $F_{1,41} = 41.55$, $p < .001$, $\eta_p^2 = .503$) and a significant learning group (explicit vs. implicit) by parameter estimate interaction ($F_{1,41} = 22.53$, $p < .001$, $\eta_p^2 = .355$). Subsidiary analysis revealed that the explicit learning group had a significantly larger rule estimate as compared to the implicit learning group ($F_{1,41} = 24.15$, $p < .001$, $\eta_p^2 = .371$) while the opposite pattern was found for the similarity estimate, i.e. larger estimates for the implicit as compared to the explicit group ($F_{1,41} = 13.73$, $p < .001$, $\eta_p^2 = .251$).

2.6. Discussion

Experiment 1 revealed several results consistent with the view that both similarity- and rule-based knowledge contributes to AGL. Confirming the first hypothesis the main findings indicate that rule estimates as derived from individual as well as from cumulative ROC curves were higher for the explicit than for the implicit learning group. Conversely, similarity estimates were higher for the implicit than for the explicit group. This latter finding replicates the results obtained by [Kinder and Assmann \(2000\)](#) demonstrating that only similarity-based processes contribute to implicit AGL. However, the results for the explicit learning group suggest that rule-based knowledge might also contribute to AGL. As detailed for the explicit learning group all four models – similarity only, rule only, and hybrid rule/similarity models – fitted the empirical data. However, the best fit was provided by the hybrid model with a significant improvement as compared to the similarity only model.

Despite such converging evidence for a dual process account there are, however, alternative accounts assuming a single knowledge representation that can be assessed in different ways ([Vokey & Higham, 2005](#)). According to this account test strings either are matched to a single prior episode, producing the similarity effects or are compared to the representation of multiple episodes to produce the grammaticality effect. Thus, both grammaticality and similarity judgments are informed by the similarity to prior instances stored in a single episodic database, but accessed through different processes. This contrasts with the view proposed here that the extraction of commonalities across multiple instances leads to an abstract rule representation (see [Sun, 1995](#); [Sun, Zhang, Slusarz, & Mathews, 2007](#) for a similar argument). Crucially, any similarity-based judgment regardless of the knowledge base relies on a continuous similarity scale which should be best described by a curvilinear ROC in line with the signal detection theory. Any rule-based judgment, in contrast, would generate a rather linear ROC. The linear component of the ROC in probability space for the explicit learning group clearly supports the assumption of a threshold process thereby suggesting the involvement of rule-based learning.

In addition to the ROC an error analysis also indicated that participants in the explicit group learned at least some rules of BROCANTO. While more than half of the participants learned the full set of grammatical rules and used these rules in the majority of their decisions the rest of the participants acquired only partial rule knowledge. We can only speculate about possible reasons but they might include interindividual variability in processing the feedback during the test blocks ([Opitz, Ferdinand, & Mecklinger, 2011](#)) or in musical training ([Brod & Opitz, 2012](#)).

There are two potential causes for the evident rule-based learning in the explicit but not in the implicit learning group. First, the explicit but not the implicit learning group encountered non-grammatical in addition to grammatical items during their training phase. Thus, the difference in performance of the implicit and explicit groups at test could in principle be a reflection of a difference in the materials they studied. This seems rather unlikely as grammatical and non-grammatical test sentences would appear equally similar if these items are not distinguishable during the training phase. This, in turn should be reflected in high endorsement rates for non-grammatical items a hypothetical pattern that is not consistent with the present results. Thus, rather than the material per se the different processes engaged during training by the explicit learning group seem to be a favourable condition for rule-based processes to be involved. It is conceivable that explicit feedback during training led to more elaborate learning and promoted rule-based classifications during test. This notion contrasts with previous results obtained for amnesic patients suggesting that rule-based abstraction processes occur implicitly ([Knowlton, Ramus, & Squire, 1992](#); [Knowlton & Squire, 1996](#)). To reconcile these conflicting results the conditions under which rule-based processes could be observed should be identified. It is conceivable that performance feedback in the present experiment promotes learning through

top-down controlled explicit hypothesis testing. Whenever a rule leads to a positive outcome (as indicated by the feedback) it will be strengthened and generalised to new instances. In contrast, if a rule leads to negative outcome it will be revised, specialised, or discounted at all. It has been argued that this type of learning requires deliberate and extensive practice (Sun et al., 2007). The second experiment tests this hypothesis by investigating how rule-based processes will develop during the course of learning.

3. Experiment 2

In Experiment 1 it was demonstrated that the overall performance in an AGL task might be determined by the interplay of similarity- and rule-based processes. As assumed by some dual-process accounts of AGL (Domangue et al., 2004; Sun, Slusarz, & Terry, 2005) implicit learning based on the similarity between the test sentence and some memory representation is a fast and relatively effortless process but with limited accuracy. In contrast, explicit learning through hypothesis testing is assumed to be rather effortful and slow. From this assumption it follows that similarity-based processes should govern the initial learning phase while rule-based processes should play a predominant role during later learning stages. Experiment 2, therefore, included a longer training phase with confidence judgments to assess performance improvements during training. It was predicted that rule knowledge is gradually developed during training and will be most evident at later stages. Similarity-based processes, in contrast, should be available from the beginning and should diminish with greater learning success.

3.1. Participants

Participants were recruited among students from Saarland University, Saarbrücken. A total of 24 monolingual, native speakers of German participated in this experiment. The participants (12 male) were from 20 to 34 years old ($M = 22.7$ years), had normal or corrected-to-normal vision and were without history of neurological or psychiatric illness.

3.2. Stimuli

The same stimulus material as in Experiment 1 was used.

3.3. Procedure

The procedure was almost identical to the one for the explicit learning group in the first experiment with two exceptions. Firstly, to achieve a longer training phase each of the 100 training sentences was presented three times across a total of 15 learning/test blocks. Secondly, confidence judgments had to be given already during the training phase. Again, visual feedback was given for each response according to the response assignment from 1, "surely grammatically correct" to 3, "somewhat grammatically correct" for the supposedly correct sentences and from 4, "somewhat grammatically incorrect" to 6, "surely grammatically incorrect" for the supposedly incorrect sentences. This response assignment was provided on every test trial as a reminder for the participant.

3.4. Data analysis

To evaluate learning related changes in the ROC data were collapsed across five training blocks yielding data for three learning phases (initial, middle and late phase). As Experiment 1 provided evidence that the hybrid model best accounts for the data of the explicit learning group only this model was considered in the present experiment. Moreover, it allows for both single process outcomes when the respective other parameter is estimated to be zero. Again parameter estimates for rule and similarity were derived from both cumulated and individual ROC curves. The latter were subjected to a repeated measure ANOVA with the factors learning phase and parameter estimate. When appropriate,

degrees of freedom were corrected according to Greenhouse–Geisser. For convenience, uncorrected degrees of freedom were reported along with the epsilon (ϵ_{G-G}) measure and the exact p -values corresponding to the corrected degrees of freedom.

3.5. Results

As shown in Table 4 the grammatical test sentences were endorsed more often than the non-grammatical sentences in all learning phases (main effect sentence type: $F_{1,23} = 169.79$, $p < .0005$, $\eta_p^2 = .881$). Moreover an increase of the endorsement rates for grammatical items together with a decrease of the endorsement rates for non-grammatical items was observed (sentence type by phase interaction: $F_{2,46} = 38.17$, $p < .0005$, $\epsilon_{G-G} = .96$, $\eta_p^2 = .624$). This indicates an increasing proficiency as learning proceeds.

The cumulated empirical ROC data in probability space could be well fitted by the hybrid model (Fig. 4). Interestingly, the ROCs were consistently higher for later training phases, again indicating that classification performance increased with longer training sessions. The ROC for the initial training phase exhibited a continuous inverted U-shape in probability space, a pattern indicative for the sole contribution of similarity-based processes. However, the ROC for the late training phase was highly asymmetrical. This suggests that the normality assumption underlying the signal-detection models was violated and the rule knowledge did contribute to classification performance at least in the late training phase.

The parameter estimates based on the cumulative ROCs were similar to the parameter estimates derived when each participant's ROC was fitted to the model, suggesting that the cumulative ROCs were representative of the individual ROCs. The average individual parameter estimates are shown in Fig. 5. A repeated measure ANOVA with the factors learning phase (initial, middle, and late phase) and parameter estimate (rule vs. similarity) revealed a significant main effect of learning phase ($F_{2,46} = 9.01$, $p = .002$, $\epsilon_{G-G} = .71$, $\eta_p^2 = .251$), a main effect of parameter estimate ($F_{1,23} = 71.03$, $p < .0005$, $\eta_p^2 = .755$) and a significant interaction of both factors ($F_{2,46} = 7.61$, $p = .001$, $\epsilon_{G-G} = .94$, $\eta_p^2 = .249$).

Table 4

Mean endorsement rates ($\pm$ SEM) for grammatical and non-grammatical sentences in each of the three learning phases.

Phase	Grammatical sentences	Non-grammatical sentences
Initial phase	.735 (.022)	.436 (.027)
Middle phase	.734 (.028)	.321 (.041)
Late phase	.813 (.031)	.232 (.033)

Fig. 4. Receiver-operating characteristics across the three training phases: initial phase – dotted line, middle phase – dashed line, late phase – solid line. Diamonds, circles and triangles represent the respective empirical data.

Fig. 5. Parameter estimates derived from formal hybrid model for individual ROCs for Experiment 2 as a function of the learning phase. Error bars represent standard errors of the means.

Follow-up analysis for each parameter estimate separately revealed a significant main effect of learning phase for rule knowledge ($F_{2,46} = 15.29$, $p < .0005$, $\varepsilon_{G-G} = .82$, $\eta_p^2 = .399$), but not for similarity knowledge ($F_{2,46} = 1.87$, $p = .167$, $\varepsilon_{G-G} = .96$, $\eta_p^2 = .075$). Furthermore, a trend analysis indicated that the rule estimate linearly increased from the initial to the late learning phase ($F_{1,23} = 29.17$, $p < .0005$, $\eta_p^2 = .599$).

3.6. Discussion

Experiment 2 tested the hypothesis that rule-based processes will gradually develop during AGL while similarity-based processes should be available from the beginning. The obtained results of a linear increase of the rule estimate as learning proceeds together with a constantly high similarity estimate confirmed this hypothesis. It further demonstrates that rule and similarity processes may operate in parallel. During initial stages of learning, when little knowledge about the abstract rule level of items is available, these abstract processes will fail to compete with the faster, more efficient similarity-based processes (Domangue et al., 2004). Therefore, the ROC during initial learning stages does reflect participants' tendency towards similarity strategies. With more extensive training (i.e., longer training in the present study) the competition efficiency of rule processes increase and might finally dominate similarity-based learning at the final stages of learning.

4. Experiment 3

The main goal of the third experiment was to test a further assumption that could be derived from the dual-process account of AGL. As has been previously shown participants employ relatively effortless and fast similarity-based processes whenever a sufficiently high accuracy could be achieved (Domangue et al., 2004). However, they could also make use of rule-based processes whenever task demands require it as was the case in the previous two experiments. In Experiment 3 a stimulus-related approach is adopted to investigate the use of rule-based processes in further detail. Previous studies usually employed regular or finite-state grammars, for which transitional dependencies between a finite set of states can generate the sequence. This restricted set of states is only capable generating a limited set of grammatical sequences, although the number of strings within each sequence might be unlimited when the alphabet is sufficiently large. Given the restricted number of different sequences that can be generated by any regular grammar, similarity-based approaches seem to be sufficient for learning such grammars. Indeed, the mastery of such regular grammars on the basis of their superficial similarity to exemplars presented during training has been previously demonstrated (Knowlton & Squire, 1994; Perruchet & Pacteau, 1990). However, more complex sequences containing for instance crossed or hierarchically embedded dependencies, which require a supra-regular or context-free grammar to generate them, are in principle unlimited in their number (Fitch & Friederici, 2012). However, this infinite number of potential structures can be described by a small set of rules. This puts in

question whether supra-regular grammars could be acquired solely predicated by way of similarity processes or whether rule-based processes are required. One study that tried to ensure rule-based processing and to prevent alternative strategies in AGL demonstrated above chance performance in classifying such supra-regular grammars (Bahlmann, Schubotz, & Friederici, 2008). Thus, it was predicted that the rule parameter of the ROC should be higher for sentences generated according to a supra-regular grammar as compared to sentences comprised of a regular grammar only.

4.1. Participants

A total of 24 monolingual, native speakers of German volunteered for this experiment. They all had normal or corrected-to-normal vision and were without history of neurological or psychiatric illness. One participant had to be excluded due to noncompliance with the instructions. Thus, only data of 23 participants (mean age 23 years, range 19–28, 5 male) entered the analysis.

4.2. Stimuli

In contrast to the stimuli used in Experiments 1 and 2 the stimuli of the present experiment were formed according to a context-free grammar. The core version of BROCANTO was modified to include a complementizer structure (*c*; see Fig. 1B) that allowed hierarchically embedded structures (Opitz & Friederici, 2007; Opitz & Kotz, 2012). In Experiments 1 and 2 a sentence [S] could be constructed by the linear concatenation of an NP, a VP and an optional second NP ($S \rightarrow NP VP [NP]$) generating an adjacent dependency. The new rule including hierarchical embedding now generates sentences that could also include a second VP (i.e., $S \rightarrow NP VP c NP VP$) thereby establishing a long-distance dependency between the complementizer and the second VP. Thus, 75 grammatical sentences and their corresponding non-grammatical counterparts exclusively comprised of adjacent dependencies were selected from the stimuli used in Experiments 1 and 2. These were complemented by 75 additional grammatical sentences with long-distance dependencies that were matched for the total number of words. The non-grammatical version of the long-distance dependency condition was rendered ungrammatical as a second VP at the end of the sentence is only licensed after a *c*-element. That is, violations of long-distance dependencies comprised sentences containing a second VP without a preceding complementizer or a complementizer not followed by a second VP.

4.3. Procedure

The procedure was the same as in Experiment 2.

4.4. Data analysis

The data analysis was carried out in an analogical way as in the two previous experiments. Thus, parameter estimates for rule and similarity were derived from both cumulated and individual ROC curves by adjusting the hybrid model to the empirical data separately for sentences containing adjacent and long distance dependencies. The derived parameters were subjected to a repeated measure ANOVA with the factors sentence type (grammatical vs. non-grammatical) and grammatical dependency (adjacent vs. long-distance).

4.5. Results

The cumulated empirical ROC data in probability space could be well fitted by the hybrid model (Fig. 6). Interestingly, the ROCs were consistently higher for adjacent dependencies compared to long distance dependencies, indicating that the regular grammar was easier to acquire than the supra regular version.

This was corroborated by analysis of the endorsement rates (see Table 5). This analysis revealed a significant main effect of sentence type ($F_{1,21} = 60.08$, $p < .0005$, $\eta_p^2 = .741$). The significant interaction of sentence type and grammatical dependency ($F_{1,21} = 22.69$, $p < .0005$, $\eta_p^2 = .519$) indicated a

Fig. 6. Receiver-operating characteristics for adjacent dependencies (triangles, solid line) and long-distance dependencies (circles, dashed line).

Table 5
Mean endorsement rates ($\pm$ SEM) for grammatical and non-grammatical sentences as a function of grammatical dependency.

Dependency	Grammatical sentences	Non-grammatical sentences
Adjacent	.813 (.032)	.331 (.029)
Long-distance	.851 (.031)	.579 (.033)

differential performance between the two grammatical dependencies (adjacent vs. long-distance). The breakdown of this interaction revealed significant main effects of sentence type for both grammatical dependencies (adjacent dependency: $F_{1,21} = 98.72, p < .0005$; long-distance dependency: $F_{1,21} = 21.51, p < .0005$) being larger for adjacent than for long-distance dependencies ($\eta^2_p = .825$, and $\eta^2_p = .506$, respectively). This indicates that participants learned to discriminate between grammatical and non-grammatical sentences for both grammars. In addition, a subsidiary analysis suggests that the difference between the two grammatical dependencies was due to higher endorsement rates for the non-grammatical versions of long-distance dependencies as compared to adjacent dependencies ($F_{1,21} = 27.63, p < .0005, \eta^2_p = .568$) while endorsement rates for grammatical sentences did not differ between the two dependencies ($F_{1,21} = 2.31, p = .159, \eta^2_p = .092$).

To compare similarity-based and rule-based learning for both types of dependencies parameter estimates based on the cumulative ROCs were determined separately for the initial, middle and late learning phases (Fig. 7). The parameter estimates were similar to the ones obtained in Experiment 2. Again an increase in rule estimates was observed for both, adjacent and long-distance dependencies, while the similarity estimates remained relatively stable (Table 6). Crucially, the rule estimates for long-distance dependencies appeared larger than those for adjacent dependencies.

This observation for the cumulative ROCs could be confirmed when average individual parameter estimates (see Fig. 8) were subjected to a repeated measure ANOVA with the factors grammatical dependency (adjacent vs. long-distance) and parameter estimate (rule vs. similarity). This analysis revealed a main effect of parameter estimate ($F_{1,21} = 19.35, p < .0005, \eta^2_p = .480$) and a main effect of grammatical dependency ($F_{1,21} = 7.36, p = .013, \eta^2_p = .260$). The interaction between the two factors approaches significance ($F_{1,21} = 3.24, p = .087, \eta^2_p = .133$). Analyses at each level of the factor estimate indicated a higher rule estimate for long distance dependencies as compared to adjacent dependencies ($F_{1,21} = 7.89, p = .011, \eta^2_p = .273$), while no differences between the two dependencies were observed for the similarity estimate ($F_{1,21} \ll 1, \eta^2_p = .001$).

4.6. Discussion

In Experiment 3 the effect of stimulus structure on the ROC parameter estimates was investigated. For this purpose long-distance dependencies between particular words in a sentence generated by a

Fig. 7. Receiver-operating characteristics across the three training phases for adjacent dependencies (left panel) and long-distance dependencies (right panel). For details see Fig. 4.

Table 6

Rule [R] and similarity [S] parameter estimates for adjacent and long-distance dependencies in each of the three learning phases.

Phase	Adjacent dependencies		Long-distance dependencies	
	R	S	R	S
Initial phase	.05	.63	.18	.69
Middle phase	.13	.90	.24	.76
Late phase	.36	1.00	.57	.81

Fig. 8. Parameter estimates derived from the formal hybrid model for individual ROCs for Experiment 3 for adjacent and long distance dependencies. Error bars represent standard errors of the means.

supra-regular grammar had to be learned in addition to adjacent dependencies generated by a regular grammar. While no differences between adjacent and long distance dependencies were observed for the similarity estimate, the rule estimate was significantly higher for the more complex supra-regular grammar. This indicates that participants utilised the extracted regularities within the training materials to correctly classify novel stimuli. Although, this might be the case for adjacent dependencies as well it seems of greater importance for long-distance dependencies. This is because the actual stimulus containing long-distance dependencies has to be compared to a large (and theoretically infinite) number of possible sentence structures that can be described, however, by a small set of rules. On

these grounds it is conceivable that this slow and laborious rule extraction process outperforms the fast but inaccurate similarity-based learning process that will necessarily fail to provide a high learning outcome in case of supra-regular grammars. Contrarily, similarity-based learning is apparently adequate to attain a certain above-chance level of proficiency of regular grammars with a limited set of possible sentence structures (Kinder & Assmann, 2000; Lotz & Kinder, 2006). In summary, the present results suggest that whenever a large (and theoretically infinite) number of comparisons have to be made to assess the similarity of word sequences participants rely on a rather small set of rules adequately describing these sequences.

5. Joint analysis of the experiments

So far, the three experiments have demonstrated that rule-based processes contribute to AGL. Moreover, they also indicated that increased rule knowledge led to superior performance in all three experiments. This was further investigated in a final analysis estimating the variance in the overall performance accounted for by both parameter estimates taking differences between the experiments into account. For this analysis the rule and similarity estimates across all experiments entered a hierarchical regression analysis treating the different experiments as a dummy coded categorical variable. In the resulting model the rule estimate accounted for 31.3% of the total variance ($F_{1,157} = 71.42$, $p < .001$; $\beta = .74$) while the similarity estimate additionally explained only 7.9% ($F_{1,156} = 20.33$, $p < .001$; $\beta = .38$). Together, the differences between experiments accounted for less than 3.5% of the performance variation ($F_{3,153} = 2.98$, $p < .05$; mean $\beta = .14$). None of the two-way interaction terms (parameter estimate by experiment) which were also included in the analysis were associated with a significant regression weight. This result indicated that overall performance in all three experiments is mainly driven by the amount of rule-based processes involved. This nicely complements previous findings demonstrating that relatively effortless and fast memory/similarity-based processes are employed whenever a sufficiently high accuracy could be achieved under the specific task constraints (Domangue et al., 2004; Kinder & Assmann, 2000). However, there seems to be a limit to the performance level that could be attained by relying on similarity-based knowledge only. A further performance increase seems to be associated with an enhanced use of rule-based knowledge. The level of performance that could be gained through similarity-based processes is not only influenced by the task demands (e.g., implicit vs. explicit learning) but seems also to be limited by the complexity of the grammar to be learned (e.g., regular vs. supra-regular grammar).

6. General discussion

Three experiments evaluated cognitive processes underlying the acquisition of word sequences following different task demands and grammar systems. This research was motivated from divergent results of previous AGL tasks that restricted the learning to conditions that might have hindered the acquisition of rules. Some of these studies found evidence for prevailing influence of superficial similarity on AGL (Kinder & Assmann, 2000; Lotz & Kinder, 2006; Pothos & Bailey, 2000) whereas other studies suggested a hybrid (rule- and similarity-driven) account of AGL (Domangue et al., 2004; Hauser, Hofmann, & Opitz, 2012; Knowlton & Squire, 1996; Mathews et al., 1989; Meulemans & van der Linden, 1997; Opitz & Friederici, 2004). The overall pattern of results, in line with the latter view, indicates that both similarity- and rule-driven processing may contribute to the acquisition of a new artificial grammar system. Across all three experiments an asymmetrical probability ROC with an accentuated linear component was obtained indicating the joint use of rule and similarity processes.

Furthermore, the present results identified some conditions under which rule-based processes could be observed. Experiment 1 indicated that immediate performance feedback in addition to observational learning benefits rule extraction and considerably enhances classification performance. At a first glance this contradicts many previous reports that informing participants about the presence of underlying grammatical rules derogates classification performance (Reber, 1976; Van den Bos & Poletiek, 2007). Further studies using a response-deadline procedure (Higham, Vokey, & Pritchard,

2000; Vokey & Higham, 2004) demonstrated equal performance for groups of participants that were instructed either to memorise the learning items or to search for the underlying grammatical rule. This indicates that even under explicit instructions rule-based processes did not contribute to overall performance. Despite this inefficiency of such general rule search instructions others have reported a substantial performance increase when specific aspects of the AGL task were emphasised (Reber, Kassir, Lewis, & Cantor, 1980; Sallas et al., 2007; Van den Bos & Poletiek, 2007). Reber et al. (1980) demonstrated an increase of correct grammaticality judgments after their participants intensively reviewed a schematic illustration of the grammar system and were explained the basic principles of constructing the letter strings (see Sallas et al., 2007 for an extension of these findings to the effect of timely delivery of grammar knowledge). Another study reported that, after being instructed to direct their attention to the relevant aspects of the letter strings, one third of the participants were at least partly able to verbally report the underlying grammatical rules while the majority of participants (about 60%) used similarity-based strategies (Nokes & Ash, 2010). Based on these results it was argued that the amount of processing dedicated to the relevant features is critical to what is learned. In other words, the more attention was given to the task-relevant aspects of the stimuli the more rule learning occurred. Together with the present results these studies suggest top-down rule-based learning in that they all emphasise learning through explicit hypothesis testing; either by providing external grammar knowledge (Reber et al., 1980; Sallas et al., 2007), by directing attention towards the relevant aspects of the letter strings (Nokes & Ash, 2010), or by providing immediate performance feedback (present study). Such top-down learning could be achieved by hypothesising a particular rule, testing it against the incoming stimuli, and utilising outcome information (e.g., feedback as in the present study or externally provided grammar knowledge as in the studies by Reber et al., 1980 and Sallas et al., 2007) to revise the rule. Only those rules will be retained that describe the grammar system to a sufficiently high degree. It should be noted that these rules are not necessarily identical to the rules generating the grammar (e.g., Dulany, Carlson, & Dewey, 1984) but have to be sufficiently accurate to allow superior classification accuracy.

In addition to learning through top-down controlled explicit hypothesis testing a recent computational model suggests that learning could also be achieved through stimulus driven bottom-up rule abstraction (Sun, Merrill, & Peterson, 2001; Sun & Zhang, 2004; Sun et al., 2007). The basic idea here is that rule knowledge can be acquired on the basis of previously acquired similarity knowledge by gradually extracting the statistical regularities across multiple exposures to sentences formed according to the artificial grammar. The results of Experiments 2 and 3, indicating initially prevalent similarity-based learning along with gradually evolving rule-based processing, are in line with this view. It is conceivable that participants in the present experiment have learned frequently occurring sequences of adjacent words, e.g. particular noun phrases like 'aaf trul' or 'aak böke plox', and initially used these as templates for their grammaticality judgment. The gradually increasing use of rule knowledge in our experiments may further suggest that during a prolonged exposure to the artificial grammar the size and complexity of these templates increases to the point that they can be unified into abstract representations of general regularities, e.g. a more abstract representation of noun phrases as *dN* or *DNM* (Dulany et al., 1984; Forkstam, Hagoort, Fernández, Ingvar, & Petersson, 2006; Hauser et al., 2012; Pothos, 2007). This abstraction of the regularities across several presentations of grammatical stimuli, although time consuming and laborious, allows generalising beyond a specific word order and results in a set of rules describing the artificial grammar to a very high degree. These rules can be viewed as an organisational scaffold for the efficient judgment of new stimuli. That is, the incoming new stimulus is no longer compared with a large number of possible sentence structures but is compared with a small set of rules. This is most important when the complexity of the stimulus set, as the long-distance dependencies in Experiment 3, allows for a theoretically infinite number of exemplars to be generated. Although the finite number of sentences used in the present experiment could in principle be represented by mere memorisation and, therefore, be accessible by similarity-based processes this strategy does not allow the generalisation to new and dissimilar instances from the infinite body of potential grammatical sequences. In contrast, regular grammars are a set of finite structures that could be wholly memorised. Although learning a finite set of rules specifying this regular grammar is beneficial for task performance it was not or at least less required to achieve an acceptable proficiency level. Crucially, as long as such rule knowledge is not evolved these abstraction processes will fail to

compete with the faster and at a low performance level more efficient similarity-based processes (Domangue et al., 2004). During the course of learning, however, the rule-based strategy may take over outperforming similarity-based learning, and resulting in better overall performance and a more linear, i.e., rule-like ROC. This was also confirmed in the joint analysis of the three experiments demonstrating that rule knowledge provides the major contribution to overall performance.

This bottom-up process of abstracting rules from particular instances was also investigated using an introspective approach (Dulany et al., 1984). In this study it was found that so-called micro-rules that describe the learned sequences to a certain degree were used by the participants to mark those parts of the sequence that render it non-grammatical (e.g., 'Strings have to begin with T or V.'). The probability of correct judgments based on these micro-rules was highly correlated with the overall performance. This indicates that participants had developed some abstract rules during learning. However, these micro-rules did only partly overlap with those rules underlying the artificial grammar. Although the present study does not allow addressing this issue in more detail, the proposal of micro-rules does not contradict the present account. Instead it could be argued that some micro-rules that only poorly describe the artificial grammar were extracted during learning but were not yet sufficiently revised during the learning process. However, further research is required to further substantiate the presented view of bottom-up and top-down rule learning.

7. Conclusions

Taken together, the present results show the suitability of the ROC method to demonstrate the actual amount of the assumed rule- and similarity-based learning mechanisms. They clearly supported the hybrid model assuming both surface information and grammatical rules to be involved in AGL. The interaction of these learning processes led to complementary knowledge representations; on a continuous dimension utilised for similarity judgments and on a discrete level forming the basis for rule-driven judgments. These two representation levels may operate in parallel and compete against each other to be utilised for grammaticality judgments. The proportion of successful classifications based on the respective level will determine the probability of selecting one or the other level for future decisions. This view bears similarities to a previously proposed cognitive architecture describing the interaction of implicit and explicit learning in a highly similar way (Sun, 1995; Sun & Zhang, 2004; Sun et al., 2001, 2005, 2007). However, the present view focuses on the representational level (rules vs. similarity) rather than on the underlying types of learning (implicit vs. explicit). Except top-down learning, which is explicit, the present view is agnostic to whether similarity-based learning or learning via bottom-up rule extraction is explicit or implicit. Previous literature provides evidence that both explicit and implicit learning might lead to similarity knowledge or abstract rule knowledge. It remains open for future research to establish a more direct link between the different types of learning and the conditions under which similarity or rule knowledge is developed.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.cogpsych.2015.02.003>.

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