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Proceedings of the Annual Meeting of the Cognitive Science Society

Title

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Permalink

Journal

ISSN

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Publication Date

2012

Peer reviewed

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Abstract

Children with Specific Language Impairment (SLIC) experience difficulties in processing Subject relative clauses (SRC). This has been interpreted as evidence that they lack syntactic representations for SRC. Our study investigates the spontaneous production of SRC in typically developing children (TDC) and SLIC in a structural priming paradigm, and compares their performance in a sentence repetition task. We demonstrate that SLIC are much more likely to produce SRC during priming than in sentence repetition; moreover, when primed, their performance matches TDC's baseline (unprimed) performance. Furthermore, we design two simple unsupervised Bayesian models, and predict the developmental group (SLI, TD) and priming condition (Primed, Non-Primed). Overall, this study shows that SLIC can spontaneously produce SRC when primed, suggesting their impairment is related to working memory, rather than a deficit in syntactic knowledge.

Keywords: specific language impairment; language development; syntactic priming; sentence repetition; Bayesian data analysis.

Introduction

Subject relative clauses (SRC) such as *the cat that's on the table* are generally early acquired, at around 3 years in typically developing children (TDC; e.g., Crain et al. 1990). However, children with Specific Language Impairment (SLIC) display difficulties in producing subject (and object) relative clauses (Novogrodsky & Friedmann, 2006). Preschool SLIC show a delayed onset of relative clause production, and frequent omission of the complementizer in both elicitation and spontaneous production (Contemori & Garraffa, 2010). This difficulty extends to repetition of sentences involving SRCs. This is particularly interesting, because recent research has suggested that in TDC, prior exposure to even difficult structures can facilitate their subsequent production (e.g., Bencini & Valian 2008). Such effects have been identified as manifestations of syntactic priming, whereby an abstract syntactic representation is facilitated (Bock, 1986). In adults, syntactic priming appears to be implicated in sentence repetition (Potter & Lombardi, 1998). It is therefore striking that SLIC do not show facilitated production of SRC in sentence repetition, as we would expect a benefit from a syntactic priming effect, enhanced by lexical repetition.

Previous research has therefore proposed that SLIC do not have a syntactic representation of SRC (Conti-Ramsden et al., 2001). In this paper, we consider an alternative hypothesis, namely that SLIC's poor performance in sentence repetition does not reflect a lack of syntactic knowledge, but rather a task-specific difficulty, which may be related to working memory demands. We investigate this hypothesis by comparing SLIC's and TDC's production of SRCs in tasks where they are explicitly elicited (in a sentence repetition task) and when they are implicitly elicited (in a picture-description syntactic priming paradigm). We use Bayesian Data Analysis to investigate our hypothesis, and design a series of Bayesian models to tackle it.

Experiment

Substantial research has used a syntactic priming paradigm to demonstrate that people use abstract syntactic representations to process language (Bock, 1986; Pickering & Branigan, 1998). In such research, speakers show an increased tendency to use a particular structure after previously encountering the same structure (even with different lexical content). These effects have been have been argued to provide evidence about syntactic representation (Branigan et al., 1995). Recent research on TDC has therefore used syntactic priming to provide evidence for the early acquisition of TDC's syntactic representations, e.g., passive constructions (e.g., Bencini & Valian 2008): If children are more likely to produce a particular structure after previous exposure to it, it implies that they have an abstract representation for that structure, which can be facilitated through residual activation or implicit learning (Chang et al., 2006; Pickering & Branigan, 1998). The former may explain short term priming effects; the latter may explain long term and cumulative priming effects. We argue that a syntactic priming paradigm can similarly be used to examine whether SLIC have access to an abstract representation of SRC, whose availability can be incremented through priming.

To do this, we used a Snap priming paradigm (Branigan et al., 2005), in which SLIC and TDC engaged in a card game that involved three elements: 1) listening to the experimenter describe a picture (using either a simple noun or an SRC), 2) describing their own picture, 3) and deciding whether or not the two pictures matched [1].

In the analysis, we assess whether the two groups (TDC, SLIC) differ in their production of SRC (Model 1); and test if any difference depends on the priming condition (i.e., whether the experimenter's description involved a simple noun or an SRC; Model 2). We expect TDC to have a higher production of SRC than SLIC. However, we expect SLIC to perform better in the primed than in the non-primed condi-

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[1] On three quarters of trials, the pictures did not match, and on one quarter - *Snap* trials - they did match

tion. If so, this would provide evidence that SLIC have a syntactic representation of SRCs, whose retrieval is facilitated by prior exposure. This in turn would imply that SLIC's observed impairments in SRC production have a different source than lack of syntactic knowledge of SRCs.

We then compare the two groups' performance on Snap trials only (i.e., where the child's picture matched the experimenter's picture, and hence the child could repeat the experimenter's description verbatim), with their performance in a task where they were explicitly asked to repeat the experimenter's sentence [2] (Model 3). Thus we compare children's production of SRC sentences, when the children produce those sentences freely in response to a picture stimulus (priming) and when they produce them as part of an explicit repetition task (repetition). If their impairment is fundamentally syntactic, then SLIC are expected to be equally bad on both tasks, and the TDC equally good on both tasks. If instead the impairment has a non-syntactic source, then children may show differential performance on the two tasks. In particular, if SLIC have a working memory impairment, they may find it difficult to produce SRC in a task where they must retain in working memory the meaning to be communicated (as well as its syntactic form).

We then investigate cumulative priming, i.e., whether the likelihood of producing an SRC increases as a function of priming instances (Kaschak et al., 2011), which is assumed to reflect implicit learning. Given previous evidence that SLIC have impairments in implicit learning (Tomblin et al., 2007), we should observe no such cumulative effect benefit in SLIC.

Finally, we move on to possible applications of our study, and investigate the problem of classification, and the related issue of diagnostic statistics to assess impairment (here, SLI). We use Bayesian inference to built two classifiers: in the first (Model 5), we categorize the development group (SLI, TD) based on the number of SR produced; and in the second (Model 6), we use the same measure to categorize development group and priming (Primed, Non-Primed). The retrieval performance of the two Bayesian models is compared with logistic regression classifiers, binomial (Model 5), and multinomial (Model 6) on F-score, an aggregate measure of precision and recall.

Method

We compared SLICs (and control TDCs) production in a syntactic priming paradigm using a picture description SNAP task. Thirty-eight (19 SLI, 19 TD) pre-school monolingual Italian children participated (mean = 5.4 years, Non-verbal IQ > 92). SLIC were selected on the basis of their general comprehension and expressive abilities, measured on MLU and on performance on standardized language tests (expressive abilities: Frog story; receptive lexicon: PPVT; receptive grammar: TCGB).

Children described target pictures after hearing the experimenter describe a prime picture with an SRC (*a cat that's on a wall*) or a simple noun (*a cat* in a within-participants manipulation (priming). There were 24 prime/target pairs (where the experimenter's and child's pictures, and hence necessarily

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[2]Conducted on the same groups of children.

their descriptions, were different), and 8 'snap' pairs (where the experimenter's and child's pictures were identical, and they could therefore use identical descriptions).

The same groups of children took also part in a sentence repetition task, where they had to repeat, verbatim, 10 SRC sentences produced by the experimenter. We compare their performance in this task with their performance on the 'snap' trials (8 per participant), in which they described the same picture as the experimenter had just described (and hence could repeat the experimenter's utterance verbatim).

Data Analysis

We adopt a Bayesian approach for the analysis of this study, with the aim of uncovering the parameters responsible for generating the observed data, (e.g., the performance of the two populations of children), infer their distribution, and have an estimate of the uncertainty in our hypothesis (Kruschke, 2010).

In the next sections, we describe four Bayesian models used to test our hypotheses. Then, we apply Bayesian analysis on a classification task and infer, in an unsupervised way, developmental group (SLIC, TDC) and priming condition (Primed, Non Primed) using the number of produced SRC as our dependent measure. We compare the performance of these two Bayesian classifiers with logistic regression models, which are trained on the same set of data. We report F-scores to assess the overall performance of the models, and precision and recall for the different classes to evaluate more in depth the classification performance.

Models

All Bayesian analyses presented here are performed using `OpenBugs` as implemented by the `R` packages `BRugs` and `R2WinBugs` (Sturtz et al., 2009; Kruschke, 2011).

Model 1: Group analysis The first model estimates how different the two groups of children (TDC, SLIC) are in producing SRC. We model the occurrence of an SRC production through a Bernoulli process (e.g., coin toss) with a given probability of success, whereby the total number of occurrences in a series of trials follows a binomial distribution. For each group of children, the number of SRC produced is denoted by the vectors x and y, which represent independent samples from two different binomial distributions, in a total of N trials ($N = 24$), with respective probabilities p and q underlying SR production. Each group consists of S observations, equal to the number of children in that group. The index i in x_i and y_i refers to subject i in each group. The likelihoods of the data are given by:

$$P(x_1, x_2, ..., x_S | p) = \prod_{i=1}^{S} \binom{N}{x_i} p^{x_i} (1-p)^{N-x_i}, \quad (1)$$

in the case of the TDC group, and an analogous equation for the SLI group by replacing p by q. As prior knowledge, we assume that both p and q are independently drawn from $\sim \text{Beta}[1,1]$. This allows us to independently estimate the underlying production rate for TDC and SLIC.

Model 2: Effects of priming In the second model, we compare the effect of priming on the production of SRC for the two groups of children. Here, our dependent measure is the number of SRC produced for each trial, i.e., we aggregated over participants. Every trial can belong to one of the two Priming states (Primed, Not Primed). So, each observation $n_t, (t = 1, ..., N)$ is the number of SRC produced in trial t, to which a particular state of priming c_t is associated: $c_t = 1$ refers to a Non-Primed trial, and $c_t = 2$ to a Primed one. Since trials are independent, and we know their priming status, given by the vector c, the likelihood of the performance of a group can be computed as a product over trials:

$$P(n_1, n_2, ... n_N | p, c) = \prod_{t=1}^{N} \binom{S}{n_t} p(c_t)^{n_t} \left(1 - p(c_t)\right)^{S-n_t} \quad (2)$$

We assume a uniform prior for $p(1)$, and the relation $p(2) = p(1) + \theta$, where the difference parameter θ, is also given a uniform prior, $\theta \sim \text{Uniform}[0, (1 - p(1))]$. We apply this model, independently to SLIC and TDC. In the former case, n is calculated from the performance of the SLIC; in the latter case, n is obtained from the TDC group. This model allows us to infer 4 parameters.

Model 3: Sentence Repetition vs Priming In this third model, adapted from Model 2, we explore more closely the role of working memory on the production of SRC by comparing SRC repetition on SNAP trials in the priming task [3], where participants could repeat the experimenter's sentence, with SRC elicited through sentence repetition.

Every trial can belong to one of the two tasks (Repetition, Priming). So, each observation $n_t, (t = 1, ..., N)$ is the number of SRC produced in trial t in Repetition ($c_t = 1$, $N = 10$) or Priming ($c_t = 2$, $N = 8$). As for Model 2, we assume a uniform prior for $p(1)$, and the relation $p(2) = p(1) + \theta$, where the difference parameter θ, is also given a uniform prior, $\theta \sim \text{Uniform}[0, (1 - p(1))]$. This model is applied independently to SLIC and TDC.

Model 4: Cumulative priming Finally, in our fourth model, we quantify the rate at which cumulative priming occurs for the two groups of children. For this model, we represent the data as two matrices X_{SxN} (TDC) and Y_{SxN} (SLI), where each entry, for example $x_{it} \in \{0, 1\}$ is a Bernoulli random variable denoting production or not of a relative clause for each subject ($i = 1, ..S$), in each particular trial ($t = 1, ..N$). We can calculate the likelihood of the data from each group, by using the following expression:

$$P(X | p_0, a, k) = \prod_{i=1}^{S} \prod_{t=1}^{N} p(t)^{x_{it}} \left(1 - p(t)\right)^{1-x_{it}} \quad (3)$$

In this model, the probability of producing an SRC is given by $p(t) = p_0 + ak(t)$, and it increases linearly with the number of priming trials $k(t)$ that have occurred up to trial t.

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[3]Note that we exclude this data from any other model of priming.

Table 1: Observed production performances (in percentage) for the two groups on the repetition and priming task (also divided by Priming condition)

Group	Repetition	Priming SNAP	Primed	Non-Primed
TDC	90%	56%	57%	19%
SLIC	16%	39%	24%	0.9%

In analogy, for the SLI group we have $q(t) = q_0 + bk(t)$. We must estimate 4 parameters: p_0, a, q_0, b. As priors, we use non-informative uniform priors for the intercepts, e.g. $p_0 \sim \text{Uniform}(0, 1)$, and normal distributions for the slopes, e.g., $a \sim \text{Normal}(0, 1)$. We expect to find a lower rate of cumulative priming for SLIC than for TDC ($a > b$), due to their impairment of implicit learning.

All models are run for 50000 iterations with a thinning of 10. If the chains have not converged, and are highly autocorrelated, we keep updating until convergence. We discard the first 5000 iterations of the Monte Carlo Markov Chains (MCMC) sample as burn-in, to calculate the posterior distribution of the parameter values. A summary of the results is reported in Table 2.

Results

Before going into the modeling results, we report the observed performance on the priming task, as well as on the repetition task for the two groups (refer to Table 1).

It is clear that during the repetition task SLIC are much more impaired than TDC in producing SRC. However, their production rates improves when we look at repetition during the priming (SNAP task) trials, where SLIC are twice as good compared to the sentence repetition result. When looking at the performance within the Priming task, we see an effect of priming on both TDC and SLIC. The production rate of SRC is more than doubled in Priming trials compared to the Non-Primed condition. These results are largely confirmed in our inferential analysis.

As expected, in Model 1 we find that $p > q$: TDC are more likely to produce SRC than SLIC (refer to Table 2). This result indicates that SLIC experience more difficulties, in fact twice more so ($p/q \approx 2$), in producing SRC than TDC. However, in order to understand whether structural priming is actually increasing the production rate of SRC in SLIC, and quantify any difference with TDC, we included the priming variable in Model 2.

Here, we find that TDC are more likely to produce SRC, especially in Primed trials. Crucially, however, we also find a strong effect of Priming in SLIC. In fact, we observe that SLIC are 20% more likely to produce an SRC when primed than when not primed. Moreover, we see that the probability of producing an SRC by a SLIC who is primed becomes indistinguishable, if not higher, than that of a TDC who is not primed. This result demonstrates that the impairment displayed by SLIC cannot be attributed to a lack of syntactic knowledge, but rather to some other aspect of cognition. In fact, when the relevant structural representations are facilitated through syntactic priming, SLIC can spontaneously pro-

duce relatively complex structures such as SRC. To examine the possible role that working memory might play in SLIC's previously observed impairment in SRC production, in Model 3, we compared syntactic priming with a task that explicitly taps working memory, namely sentence repetition.

The result of Model 3 clearly shows that the SLIC perform very differently in the two tasks, Snap and repetition (see Table 2). This is especially evident when looking at the difference in probability between the two tasks: SLIC are much more likely to produce an SRC during the Snap task than during the repetition task, whilst for TDC, the difference $p(2) - p(1)$ is almost negligible.

This result is intriguing as it implies that given a task in which the child has to actively retrieve syntactic material to communicate a contextually supported proposition (provided by the visual stimulus), their impairment is much less pronounced. This pattern is consistent with a working memory impairment in which SLIC children have difficulty in building, maintaining, and retrieving a representation of an entire sentence. In order to better explore the role of working memory on the production rate, we turn to cumulative priming. If implicit learning, which is hypothesized to underlie long term and cumulative priming effects, is impaired in SLIC, then we might observe a weaker, or almost null, effect of cumulative priming in that group.

Interestingly, the results of Model 4 show that the intercept parameter p_0, which indicates the baseline probability for TDC to produce an SRC, is markedly lower than the value observed in the previous model (refer to Table 2 for the list of models). The intercept q_0, instead, is reasonably similar in value across the two models. When we look at the slope parameters (a, b), we observe a different rate for the two groups of children. In particular, TDC experience more cumulative priming in producing SRC, compared to SLI children. This result indicates that although cumulative priming occurs in both groups, this effect is more prominent in TDC. Moreover, it seems that cumulative priming plays a crucial role on the likelihood of producing SRC, as it emerges when comparing the estimates of this model with Model 1. The diminished effect of cumulative priming in SLIC is in keeping with evidence that SLIC have impaired implicit learning. At the intercepts, in fact, the two groups display a similar probability of producing SRC, and the difference becomes more prominent when previous exposure to SRC increases.

In the next section, we shift the focus from quantification to prediction, and apply Bayesian analysis to make inferences about our data. In particular, we implement two Bayesian classifiers to predict development group and priming in an unsupervised way, i.e., we assume there is no prior knowledge about such classification, and we want to infer it from the data. In order to validate the performance of such models, we compare the classification performance of the two Bayesian models with the output of logistic classifiers. We report the F-score, which is a measure of test's accuracy based on the weighted average of precision and recall: $F = 2 \cdot \frac{precision \cdot recall}{precision + recall}$. Precision is the fraction of retrieved instances that are relevant, e.g., the number of correctly categorized children in a certain group, $\frac{tp}{tp+fp}$, and recall is the

Table 2: Mean and 95% **H**ighest **D**ensity **I**ntervals for the posterior distributions of parameters for the different models.

Parameter	Mean	95%HDI
Model 1: Groups		
p_{TD}	0.4655	$(0.4195, 0.5116)$
q_{SLI}	0.2490	$(0.2104, 0.2900)$
Model 2: Priming		
$p_{TDPrimed}$	0.6392	$(0.5747, 0.7018)$
$p_{TDNotPrimed}$	0.2961	$(0.2397, 0.3577)$
$q_{SLIPrimed}$	0.3521	$(0.2924, 0.4153)$
$q_{SLINotPrimed}$	0.1479	$(0.1052, 0.1958)$
Model 3: Task Comparison		
p_{TDSnap}	0.7639	$(0.7165, 0.8086)$
$p_{TDRepetition}$	0.7575	$(0.7086, 0.8021)$
$q_{SLISnap}$	0.4020	$(0.3216, 0.4844)$
$q_{SLIRepetition}$	0.1672	$(0.1052, 0.1958)$
Model 4: Cumulative Priming		
$p0_{InterceptTD}$	0.2702	$(0.1926, 0.3566)$
$q0_{InterceptSLI}$	0.2085	$(0.1344, 0.2870)$
$a_{SlopeTD}$	0.0357	$(0.0226, 0.048)$
$b_{SlopeSLI}$	0.0035	$(-0.0049, 0.0199)$
Model 5: Group Inference		
p_{TD}	0.4494	$(0.4030, 0.5060)$
q_{SLI}	0.2034	$(0.1429, 0.2743)$
Model 6: Group and Priming Inference		
$p_{TDPrimed}$	0.2707	$(0.2274, 0.3216)$
$p_{TDNotPrimed}$	0.2143	$(0.1467, 0.2828)$
$q_{SLIPrimed}$	0.1549	$(0.1019, 0.2316)$
$q_{SLINotPrimed}$	0.1130	$(0.084, 0.1413)$

fraction of relevant instances that have been retrieved, $\frac{tp}{tp+fn}$, e.g., the correctly categorized children off the total number of possible children in that group; where tp (true positive) is the number of instances correctly retrieved, fp (false positive) are the instances wrongly retrieved and fn those instances which should have also been retrieved. We report precision and recall for each category to distinguish what the model found easier to classify, from what found it more difficult.

Inference of developmental categories and priming

In the first Bayesian classifier (Model 5), our goal is to predict the development group of a child (SLI, TD) by considering blindly their SR production scores. Therefore, we don't assume a-priori that there is a division between TD and SLI, and mix the data between the two different groups. Our task is to infer correctly which data belongs to each category. We implement an extension of Model 1 as follows.

To each observation $z_i, (i = 1, ..., 2S)$, corresponding to the

number of SR clauses produced by all subjects of the experiment, we assign a hidden state $c_i \in \{1, 2\}$, which refers to the subject being an SLI (1) or a TD (2). If the hidden state of each subject is known, the total likelihood of the data can be computed as:

$$P(z_1, z_2, \ldots | c_1, c_2, \ldots) = \prod_{i=1}^{2S} \binom{N}{z_i} p(c_i)^{z_i} \left(1 - p(c_i)\right)^{1-z_i} \quad (4)$$

where $p(1)$ is the probability of producing a relative clause in the SLI group, and $p(2)$ of the TD group. This corresponds to a mixture model, where we infer the two distributions present in the data set (estimate p) and the probabilities $\pi_i(1)$ and $\pi_i(2)$ that each observation z_i belongs to distribution 1 or 2 (estimate c). We assume a Dirichlet prior for the category assignment and a uniform distribution for p, similar to previous models.

The final model (Model 6) is an extension of Model 5, where, beside the development group, we want to infer also the priming condition (Primed, Non Primed). So, the only real difference is that we assume four categories $c_i \in \{1, 2, 3, 4\}$ where 1 is SLI-Non priming, 2 is SLI-Priming, 3 is TD-Non Priming and 4 is TD-Priming. Again, the model is blind to these categories, and our goal is to infer them from the data. We proceed as in Model 5 and we obtain a posterior (discrete) distribution for the categorical classification of each observation, namely what is the probability that an observation comes from category 1, 2, 3 or 4. The most likely category for each observation can be obtained by considering the median of such a posterior distribution, i.e. the category that obtains a probability higher than 1/2 for that observation.

Model performance We compare the categorization performance of these two unsupervised models against two fully supervised logistic classifiers, Binomial (BL) for Model 5, and multinomial (ML) for model 6. The logistic classifiers are built using the R libraries `glm` and `mlogit`. We first fit a generalized linear model, binomial with logit link, and a multinomial regression to obtain the regression coefficients. Our dependent measure is the number of SRC produced and the independent predictor is the category: group for the binomial logistic classifier, group and priming for the multinomial classifier.

From the regression coefficients, we derive the logits, which exponentiated give us the unscaled probabilities of observing a certain category, e.g., SLI, associated to a certain SR production score. The unscaled probabilities are normalized to range between 0 and 1 [4].

For the sake of completeness, we compare the estimates of the parameters for these two models, where categories have to be inferred, with those where such information was explicitly modeled (Model 1 and Model 2); see Table 2 for the actual values. We observe that the estimates are close between

[4] More details can be found on the online tutorial provided by UCLA: Academic Technology Services, http://www.ats.ucla.edu/stat/r/dae/mlogit.htm

Table 3: Classification Performance of the Bayesian Models and the Logistic classifiers: F-scores, precision (left value) and recall (right value) for the different categories (TD and SLI): where P (Primed) and N-P (Non Primed)

(a) Model 5 vs Binomial Classifier

		Categories	
Model	**F-score**	**TD**	**SLI**
Model 5	0.85	(0.8, 0.84)	(0.83, 0.78)
BL	0.85	(0.8, 0.84)	(0.83, 0.78)

(b) Model 6 vs Multinomial Classifier

		SLI N-P	**SLI P**	**TD N-P**	**TD P**
Model 6	0.55	(0.76, 0.88)	(0.42, 0.15)	(0.35, 0.26)	(0.53, 0.94)
ML	0.56	(0.65, 0.78)	(0.36, 0.47)	(0.4, 0.21)	(0.83, 0.78)

Model 1 and Model 5; whereas there is a more marked difference between Model 2 and Model 6. As the number of categories to be inferred from the data increases, the task becomes more challenging.

When comparing the classification performance, we find that Model 5 and BL are perfectly equivalent, both in terms of F-score, and on the precision and recall of the group category. Obviously, the main outstanding difference is that the Bayesian model is unsupervised, while the logistic classifier is fully supervised. Moreover, it is interesting to notice that SLIC and TDC are recognizable as separate populations, rather than being outliers of the same distribution.

On the multi-class task, in contrast, we find that ML is slightly better than Model 6 on the F-score. When looking at precision and recall for the different classes, we find both models achieving higher classification performances on the two most extreme classes (SLI Non Primed and TD Primed), with Model 6 having a better recall than ML, which instead has a better precision. It is interesting to notice that both models fail to account for the two categories SLI Primed and TD Non Primed. The reason is that SLIC Primed perform as as well as TDC Non primed. This result confirms further our main hypothesis that SLIC have syntactic knowledge of SRC, and can achieve performance comparable to TDC when the relevant representations are facilitated through syntactic priming.

General Discussion

Typically developing children are able to process SRC around the age of 3 years (Crain et al., 1990). Yet children with SLI show difficulties with these structures at the same age (Novogrodsky & Friedmann, 2006). In particular, the finding that SLIC cannot repeat verbatim SRC sentences produced by an experimenter has been taken as evidence that SLIC do not have a syntactic representation of relative clauses (Conti-Ramsden et al., 2001). To challenge this claim, we compared SLIC and TDC's production of SRCs in two different tasks, one of which implicitly elicited repetition of SRC sentences (syntactic priming in a 'Snap' task) and one of which explic-

itly elicited repetition of SRC sentences (sentence repetition task), in a series of Bayesian Models. We then used such models to infer developmental group and priming condition on a trial-by-trial basis by looking at the number of SRCs produced.

We found that although TDC display a higher production of SRC than SLIC (Model 1), SLIC nevertheless are more likely to produce an SRC when primed, i.e., after hearing an SRC (with different lexical content) than after hearing a simple noun (Model 2). This suggests that SLIC have an abstract representation of SRC that they can recruit during production, when it has been facilitated through previous use. Crucially, however, SLIC performed worse in a sentence repetition task than in 'snap' priming trials in which they could repeat verbatim the experimenter's sentence(Model 3). In other words, the same children who performed poorly in a task that required explicit repetition of sentences performed significantly better in a priming task, where implicit repetition could be realized through incremental production of a sentence and did not require the (meaning and structure of the) entire sentence to be maintained in working memory. This suggests that SLIC's impairment on these structures is related to working memory. Furthermore, we found that whereas TDC showed a large cumulative priming effect (i.e., were much more likely to produce an SRC after several exposures), SLIC showed a markedly reduced, if not negligible, cumulative effect (Model 4).

Taken together, our results suggest that SLIC's poor performance on SRCs may reflect a working memory impairment that affects on-line processing, rather than the absence of a syntactic representation for SRCs (i.e., a deficit in syntactic knowledge). In a task that implicates all stages of language production, and in which production can occur incrementally without the necessity of retaining in working memory a representation of the entire sentence, SLIC are able to spontaneously produce SRCs after being exposed to them; furthermore, their spontaneous production of SRCs in this context is less impaired than their elicited repetition of SRCs, relative to TDC. However, the finding that SLIC show reduced cumulative priming suggests that they may also have impaired implicit learning, which may have far-reaching implications for their acquisition of language. The classification performance of our Bayesian models demonstrates moreover that we can infer the developmental group of a child very accurately (Model 5) with the same accuracy as a Binomial Logistic Classifier, with the clear advantage that the Bayesian model is unsupervised. Crucially, our classification performance degrades when trying to infer the group and the Priming condition (Model 6), because SLIC Primed perform as well as TDC Non-Primed.

In conclusion, we suggest that modeling differences in syntactic performance in syntactic priming and other experimental paradigms has great potential for investigating the nature of impairments in syntactic representations versus other aspects of cognition in SLIC and other atypical populations.

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