The Learnability of Abstract Syntactic Principles

Amy Perfors, Joshua B. Tenenbaum, Terry Regier

Presented by Prutha Deshpande

Poverty of Stimulus (PoS) Argument

- Language learners make grammatical generalizations that go beyond what is immediately justified by the evidence in the input.
- For example: children appear to favor hierarchical rules of language over linear rules, even in the absence of evidence for this preference.
- This suggests that learners may innately know such things as an organizing principle of language.

Goal of the Paper

- Reevaluate the PoS argument for innate language-specific knowledge by formalizing the problem of language acquisition within a Bayesian framework for rational inductive inference.
- Consider an ideal learner with the following domain-general capacities:
 - 1. Can represent structured grammars of various forms
 - 2. Does Bayesian statistical inference
- Argue that certain core aspects of linguistic knowledge can be inferred without language-specific capabilities.

Highlights of the Approach

- 1. Consider the learnability of entire grammars, rather than the learnability of any specific linguistic rule.
- 2. The question of whether human learners have language-specific or domain-general knowledge is separable from the question of whether linguistic knowledge is structured or unstructured.



Auxiliary Fronting

• Movement of auxiliary verb to the front of the sentence:

(1a) The man was hungry.(1b) Was the man hungry?(2a) The boy is smiling.(2b) Is the boy smiling?

• With two identical auxiliary verbs:

(4a) The boy who is smiling is happy.*(4b) Is the boy who smiling is happy?(4c) Is the boy who is smiling happy?

Auxiliary Fronting

- There is not a unique way to characterize declarative and interrogative forms.
- Complex interrogative sentences are not common in child-directed speech.
- In spite of PoS, children can form correct complex (data) interrogative sentences and do not produce incorrect forms.
- Children must have some innate knowledge of the hierarchical structure of phrases.
- What is the nature of this innate bias?



Main Results

- 1. An unbiased learner that can represent both linear and hierarchical grammars, can infer that the hierarchical grammar is a better fit to typical child-directed input.
 - → It is possible to acquire domain-specific knowledge about the form of representations via domain-general learning mechanisms.
- 2. Hierarchical phrase-structure grammar succeeds in the auxiliary fronting task even when no direct evidence is available in the input data.

Method



• Inferences from D to G and T captured by joint posterior probability:

 $p(G,T|D) \propto_p (D|G)_p (G|T_p(T)).$

The Corpora

- Adam corpus of the CHILDES database.
- Each word replaced by its syntactic category.
- Ungrammatical and grammatically complex sentences removed.
- Six corpus levels: depending on token frequency.
- Five corpus epochs: depending on age of the child.

Hypothesis Space of Grammars

- 1. To represent grammars with hierarchical phrase-structure
 - Context-free grammars
- 2. To represent grammars without hierarchical phrasestructure
 - Regular grammars finite-state grammars
 - FLAT grammar
 - One-state (1-ST) grammar



Hand-designed grammars:

Corpus	Probability	FLAT	REG-N	REG-M	REG-B	1-ST	CFG-S	CFG-L
Level 1	Prior	-99	-148	-124	-117	-94	-155	-192
	Likelihood	-17	-20	-19	-21	-36	-27	-27
	Posterior	- 116	-168	-143	-138	-130	-182	-219
Level 2	Prior	-630	-456	-442	-411	-201	-357	-440
	Likelihood	-134	-147	-157	-162	-275	-194	-177
	Posterior	-764	-603	-599	-573	- 476	-551	-617
Level 3	Prior	-1198	-663	-614	-529	–211	-454	-593
	Likelihood	-282	-323	-333	-346	–553	-402	-377
	Posterior	-1480	-986	-947	-875	– 764	-856	-970
Level 4	Prior	-5839	-1550	-1134	-850	-234	-652	-1011
	Likelihood	-1498	-1761	-1918	-2042	-3104	-2078	-1956
	Posterior	-7337	-3311	-3052	-2892	-3338	- 2730	-2967
Level 5	Prior	-10,610	-1962	-1321	-956	-244	-732	-1228
	Likelihood	-2856	-3376	-3584	-3816	-5790	-3917	-3703
	Posterior	-13,466	-5338	-4905	-4772	-6034	- 4649	-4931
Level 6	Prior	-67,612	-5231	-2083	-1390	-257	-827	-1567
	Likelihood	-18,118	-24,454	-25,696	-27,123	-40,108	-27,312	-26,111
	Posterior	-85,730	-29,685	-27,779	-28,513	-40,365	-28,139	- 27,678

• To what extent are these results dependent on particular handdesigned grammars? Local search from hand-designed grammars:

Corpus	Probability	FLAT	REG-N	REG-M	REG-B	1-ST	CFG-S	CFG-L
Level 1	Prior	-99	-99	-99	-99	-94	-133	-148
	Likelihood	-17	-19	-20	-19	-36	-26	-25
	Posterior	- 116	-118	-119	-118	-130	-159	-173
Level 2	Prior	-630	-385	-423	-384	-201	-355	-404
	Likelihood	-134	-151	-158	-155	-275	-189	-188
	Posterior	-764	-536	-581	-539	- 476	-544	-592
Level 3	Prior	-1198	-653	-569	-529	-211	-433	-521
	Likelihood	-282	-320	-339	-346	-553	-402	-380
	Posterior	-1480	-973	-908	-875	- 764	-835	-901
Level 4	Prior	-5839	-1514	-1099	-837	-234	-566	-798
	Likelihood	-1498	-1770	-1868	-2008	-3104	-2088	-1991
	Posterior	-7337	-3284	-2967	-2845	-3338	- 2654	-2789
Level 5	Prior	-10,610	-1771	-1279	-956	-244	-615	-817
	Likelihood	-2856	-3514	-3618	-3816	-5790	-3931	-3781
	Posterior	-13,466	-5285	-4897	-4772	-6034	- 4546	-4598
Level 6	Prior	-67,612	-5169	-2283	-1943	-257	-876	-1111
	Likelihood	-18,118	-24,299	-25,303	-25,368	-40,108	-27,032	-25,889
	Posterior	-85,730	-29,468	-27,586	-27,311	-40,365	-27,908	- 27,000

Regular grammar by automated search:

REG-AUTO				Other best grammars (posterior).						
Corpus	Prior	Likelihood	Posterior	FLAT	REG-N	REG-M	REG-B	1-ST	CFG-S	CFG-L
Level 1	-105	-18	-123	-116	-118	-119	-118	-130	-159	-173
Level 2	-302	-193	-495	-764	-536	-581	-539	-476	-544	-592
Level 3	-356	-505	-841	-1480	-973	-908	-875	-764	-835	-901
Level 4	-762	-2204	-2966	-7337	-3284	-2967	-2845	-3338	-2654	-2789
Level 5	-1165	-3886	-5051	-13,466	-5285	-4897	-4772	-6034	-4546	-4598
Level 6	-3162	-25,252	-28,414	-85,730	-29,468	-27,586	-27,311	-40,365	-27,908	-27,000

- A context-free grammar always has the highest posterior probability on the largest type-based corpus, compared to plausible linear grammars.
- Though the ability of the hierarchical phrase-structure grammars to generate a higher variety of sentences from fewer productions typically results in a lower likelihood, this compression helps in the prior.
- This type of grammar thus consistently maximizes the tradeoff between data fit and complexity.

Sentence tokens vs. sentence types

- Evaluate a grammar based on how well they account for which sentences occur, rather than their frequency distribution.
- Linear grammars were preferred to context-free grammars.
- The context-free grammars overgeneralize the data has more tokens, but not more variety.
- This suggests that if the hierarchical phrase structure of syntax is to be inferred from observed data, the learner may need to have a disposition to evaluate grammars with respect to type-based rather than token-based data.

Age-based stratification:

Corpus	Probability	FLAT	REG-N	REG-M	REG-B	1-ST	CFG-S	CFG-L
Epoch 0 (2;3)	Prior	-3968	-1915	-1349	-1166	-244	-698	-864
	Likelihood	-881	-1265	-1321	-1322	-2199	-1489	-1448
	Posterior	-4849	-3180	-2670	-2488	-2433	- 2187	-2312
Epoch 1 (2;3–2;8)	Prior	-22,832	-3791	-1974	-1728	-257	-838	1055
	Likelihood	-5945	-7811	-8223	-8164	-13,123	-8834	8467
	Posterior	-28,777	-11,602	-10,197	-9892	-13,380	-9672	9522
Epoch 2 (2;3–3;1)	Prior	-34,908	-4193	-2162	-1836	-257	-865	-1096
	Likelihood	-9250	-12,164	-12,815	-12,724	-20,334	-13,675	-13,099
	Posterior	-44,158	-16,357	-14,977	-14,560	-20,591	-14,540	- 14,195
Epoch 3 (2;3–3;5)	Prior	-48,459	-4621	-2202	-1862	-257	-876	-1111
	Likelihood	-12,909	-17,153	-17,975	-17,918	-28,487	-19,232	-18,417
	Posterior	-61,368	-21,774	-20,177	-19,780	-28,744	-20,108	- 19,528
Epoch 4 (2;3–4;2)	Prior	-59,625	-4881	-2242	-1903	-257	-876	-1111
	Likelihood	-15,945	-21,317	-22,273	-22,293	-35,284	-23,830	-22,793
	Posterior	-75,570	-26,198	-24,515	-24,196	-35,541	-24,706	- 23,904
Epoch 5 (2;3–5;2)	Prior	-67,612	-5169	-2283	-1943	-257	-876	-1111
	Likelihood	-18,118	-24,299	-25,303	-25,368	-40,108	-27,032	-25,889
	Posterior	-85,730	-29,468	-27,586	-27,311	-40,365	-27,908	- 27,000

Generalizability:

• The percentage of the full (Level 6) corpus that can be parsed by the best grammars learned for subsets (Level 1–5) of the full corpus.

Grammar	FLAT (%)	REG-N (%)	REG-M (%)	REG-B (%)	1-ST (%)	CFG-S (%)	CFG-L (%)
% types							
Level 1	0.3	0.7	0.7	0.7	100	2.4	2.4
Level 2	1.4	3.7	5.1	5.5	100	31.5	16.4
Level 3	2.6	9.1	9.1	32.2	100	53.1	46.8
Level 4	10.9	50.7	61.2	75.2	100	87.6	82.7
Level 5	18.7	68.8	80.3	88.0	100	91.8	88.7
% tokens							
Level 1	9.9	32.6	32.6	32.6	100	40.2	40.2
Level 2	21.4	58.8	61.7	60.7	100	76.4	69.7
Level 3	25.4	72.5	70.9	79.6	100	87.8	85.8
Level 4	34.2	92.5	94.3	96.4	100	98.3	97.5
Level 5	36.9	95.9	97.6	98.5	100	99.0	98.6

Generalizability:

• Do context-free grammars simply generalize more than the regular grammars, or do they generalize in the right way?

Туре	In input?	Example	Can parse?						
			FLAT	REG-N	REG-M	REG-B	1-ST	CFG-S	CFG-L
Decl Simple	Y	Eagles can fly. (n aux vi)	Y	Y	Y	Y	Y	Y	Y
Int Simple	Y	Can eagles fly? (aux n vi)	Y	Y	Y	Y	Y	Y	Y
Decl Complex	Y	Eagles that are alive can fly. (n comp aux adj aux vi)	Y	Y	Y	Y	Y	Y	Y
Int Complex	Ν	Can eagles that are alive fly? (aux n comp aux adj vi)	Ν	Ν	Ν	N	Y	Y	Y
Int Complex	Ν	*Are eagles that alive can fly? (aux n comp adj aux vi)	Ν	Ν	Ν	Ν	Y	Ν	Ν

Linguistic adequacy:

• Compare accuracy of grammars on a gold standard parsed corpus.

Automatically parsed				Hand-parsed			
Grammar	Precision	Recall	<i>F</i> -score	Grammar	Precision	Recall	F-score
CFG-L	51.8	94.1	66.8	CFG-L	89.6	90.4	90.0
CFG-S	50.8	92.3	65.6	CFG-S	88.3	89.1	88.7
REG-B	50.1	90.8	64.6	REG-B	85.1	85.6	85.3
REG-M	50.1	90.8	64.6	REG-M	85.1	85.6	85.3
REG-N	49.4	89.6	63.7	REG-N	84.1	84.5	84.3
RB	50.7	92.4	65.5	RB	86.9	87.3	87.1
LB	32.0	62.9	42.4	LB	33.1	33.6	33.4

Appendix A

Table A1

Sample merges for context-free and regular grammars. Identical merges for right-hand side items were also used.

CFG merge ex	ample	REG merge example			
Old	New	Old	New		
$\begin{array}{l} A \rightarrow B \ C \\ A \rightarrow B \ D \\ A \rightarrow B \ E \end{array}$	$\begin{array}{l} A \rightarrow B \ F \\ F \rightarrow C \\ F \rightarrow D \\ F \rightarrow E \end{array}$	$\begin{array}{l} A \rightarrow b \ C \\ A \rightarrow b \ D \\ A \rightarrow b \ E \\ C \rightarrow g \ E \\ D \rightarrow d \\ E \rightarrow e \ D \end{array}$	$A \rightarrow b F$ $F \rightarrow d$ $F \rightarrow g E$ $F \rightarrow e D$		

Appendix B





Appendix B

$$p(G|T) = p(n) \prod_{k=1}^{n} p(P_k) p(\theta_k) \prod_{i=1}^{P_k} p(N_i) \prod_{j=1}^{N_i} \frac{1}{V}.$$
(2)

$$p(1-p)^{n-1}$$
 (3)

$$p(D|G) = \prod_{l=1}^{M} p(S_l|G).$$
 (4)

$$P(w|\theta) = \sum_{z,\ell} \left(\prod_{k=1}^{K(z)} \theta_{\ell_k} \right) \cdot \frac{\Gamma(K(z))}{\Gamma(N)} \cdot a^{K(z)-1} \\ \cdot \left(\prod_{k=1}^{K(z)} \frac{\Gamma(n_k^{(2)} - a)}{\Gamma(1 - a)} \right)$$
(5)

Appendix B





Fig. B2. The unit simplex for $m_k = 3$ (a triangle), corresponding to the Dirichlet distribution with $\alpha = 1$ on a θ_k vector of production-probability parameters with three productions.

Fig. B3. Top: one cannot compare the probability of continuous points A and C with different dimensionality. Bottom: when A and C correspond to discrete points, comparison is possible.