

Do Construction Distributions Shape Formal Language Learning In German BabyLMs?

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Abstract

We analyze the influence of utterance-level construction distributions in German child-directed speech on the resulting formal linguistic competence and the underlying learning trajectories for small language models trained on a novel collection of developmentally plausible language data for German. We find that trajectories are surprisingly robust for markedly different distributions of constructions in the training data, which have little effect on final accuracies and almost no effect on global learning trajectories. While syntax learning benefits from more complex utterances, lexical learning culminates in better scores with more fragmentary data. We argue that LMs trained on developmentally plausible data can contribute to debates on how rich or impoverished linguistic stimuli actually are.

1 Introduction

One of the most contentious issues in language acquisition is the relationship between the input that the learner receives and the resulting linguistic system. Child-directed speech (or *CDS*) is structurally simple and, especially in the first three years of life, abounds with questions, imperatives, and fragmentary utterances, but features very few complex sentences (Cameron-Faulkner et al., 2003; Bunzeck and Diessel, 2024). This distribution of utterance-level constructions is conducive to the *functional* side of language acquisition: caregivers talk in this way to elicit responses, steer behavior or establish joined attention. But how do children acquire full-fledged, *formal* grammatical knowledge from such supposedly skewed input? Generativist approaches see this kind of stimulus as too impoverished to kickstart formal linguistic development and assume an underlying, innate grammatical endowment that enables it (cf. Chomsky, 1965; Crain and Pietroski, 2001; Thomas, 2002; Berwick et al., 2011), whereas usage-based scholars argue that domain-

general learning mechanisms are sufficient to develop a full-fledged mental linguistic system from this input, which is rich enough (cf. MacWhinney, 2004; Tomasello, 2005).

The connectionist “renaissance”, fueled by the increased adoption of deep learning and transformer language models, has opened up new avenues of addressing such questions (Warstadt and Bowman, 2022). Developmental AI (Dupoux, 2018) and the BabyLM community (Warstadt et al., 2023; Hu et al., 2024; Charpentier et al., 2025) have demonstrated that supposedly *tabula rasa* learners can indeed acquire syntactic structures, the formal side of language, successfully from very little data (Huebner et al., 2021), but without tapping into the functional side of language (Mahowald et al., 2024). This makes them ideal testbeds for the aforementioned issue: is the construction distribution found in child-directed speech really too impoverished to learn formal linguistic capabilities, and are other, more complex registers, e.g. book text (Cameron-Faulkner and Noble, 2013; Noble et al., 2018), a richer and more beneficial form of input?

To investigate this, we compile a novel German BabyLM training set, for which we conduct the first utterance-level construction analysis for German. We find that distributions align with findings for English and other languages, and that child-directed media (e.g., children’s encyclopedias) provide a construction-level middle ground between CDS and more complex book text. We then create three 5M-token subsets with distinct constructional profiles, e.g., varying the proportion of fragmentary and complex utterances, and train small, character- and subword-level Llama models on them. Our evaluation with lexical, syntactic, and semantic minimal pairs (Bunzeck et al., 2025; Mueller et al., 2020; He et al., 2025) reveals that differences between grammatically complex training data and a developmentally plausible constructional distribution are fairly small. While cer-

tain syntactic phenomena are learned somewhat better from more complex sentences, lexical learning improves with more fragments and questions in the input. Most interestingly, input complexity only modulates the steepness of the resulting learning trajectories, but has no principal effect on the amount of input needed to kickstart learning.

2 Constructions in children’s input

Child-directed speech can be seen as a separate linguistic register and is the primary input that children encounter in their first years. It has mostly been scrutinized from phonetic and lexical viewpoints, where well-established findings are that it features slower speech and exaggerated intonation patterns which infants prefer listening to (Zangl and Mills, 2007), while its vocabulary is rather restricted to everyday topics and children’s immediate surroundings (Snow and Ferguson, 1977). Structurally, child-directed utterances are usually shorter and simpler than adult-directed ones (Genovese et al., 2020) and feature high amounts of structural and lexical repetition (Tal et al., 2024). Statistical properties of the input directly influence the children’s order of acquisition for syntactic patterns (Huttenlocher et al., 2002; Ambridge et al., 2015), e.g. for relative clauses (Diessel and Tomasello, 2000; Brandt et al., 2008; Chen and Shirai, 2015).

Early studies were mostly concerned with mapping out how much CDS is ungrammatical or otherwise “wrong” (in the sense of hesitations, false starts, etc., cf. Pine, 1994), but the quantitative turn in linguistics (Janda, 2013) has enabled more holistic analyses. In a seminal study, Cameron-Faulkner et al. (2003) analyze utterance-level constructions in child-directed English via a large corpus of toyplay sessions featuring children and their caregivers. They show that CDS features only few “canonical” SV(X)-utterances but abounds with questions, lexical fragments, or copula constructions. The reported construction distributions also hold for typologically different languages, e.g., Irish (Cameron-Faulkner and Hickey, 2011). These constructions and their real-world functions help children to quickly understand the functional side of language. On the other hand, the most common and repetitive utterances that English-speaking children hear from their mothers represent a rather skewed sample of the presumed, underlying formal language system. Generativist approaches would

argue that certain formal structures, e.g. question formation from relative clauses, are not attainable from this kind of language, as the input never contains specific examples (Chomsky, 1980) (although Pullum and Scholz (2002) argue that the input frequently contains exactly such specific examples). Conversely, constructivist approaches, which view language learning as the re-construction of the target language (Behrens, 2021), argue that this kind of input is actually conducive to formal aspects of acquisition, by providing anchor points for first words and their semantic links to real-world reference, which then serve as building blocks for a gradual development into larger schemas (like questions with relative clauses).

Although CDS features such a skewed construction distribution, written language aimed at children, i.e., in the form of children’s books, is characterized by a much higher rate of canonical SV(X)-constructions than found in CDS (Cameron-Faulkner and Noble, 2013). In contrast, questions rarely occur in books. CDS produced in shared book reading presents a middle-ground — it contains more complex and SV(X)-constructions than regular CDS, but less than book text alone (Noble et al., 2018). They argue that shared reading therefore plays an important role in moving children from early, isolated traces of linguistic knowledge to a rich mental language system. This also aligns with the findings by Bunzeck and Diessel (2024), who show that the distribution of constructions in CDS varies with situation type (toyplay features most questions, meal sessions beget more imperatives, shared book reading features more complex constructions) and child age (questions and imperatives become less frequent with age). They suggest that CDS is therefore adapted to support children’s cognitive and linguistic development. Yet, as corpus studies are necessarily descriptive and cannot establish causal/mechanistic connections on their own (e.g. what would happen if a child never hears CDS), it remains questionable if this is actually true.

3 Input in developmentally plausible LMs

Authentic data Early approaches to modeling language acquisition with neural networks used hand-picked, manually ordered data points (Rumelhart and McClelland, 1986) or synthetic data generated with hand-crafted grammars (Elman, 1993; Christiansen and Chater, 1999; Chang et al., 2006).

Both lack developmental plausibility. Since then, data availability has improved with the establishment of developmental corpora. Frequently, CDS from the CHILDES database (MacWhinney, 2000) is used to train developmentally plausible LMs (cf. Pannitto and Herbelot, 2020; Huebner et al., 2021). While CHILDES-based models have the advantage of learning from authentic data *only*, they have the disadvantage of not accessing the *full breadth* of the linguistic input children receive. Children are exposed to many more different registers of language throughout their linguistic development, like the aforementioned shared (or solitary) book reading, or television shows (Montag, 2019; Gowenlock et al., 2024). As a response to this, the BabyLM corpora propose a data mix of varied spoken and written sources, from CDS over adult-adult conversations to OpenSubtitles (Lison and Tiedemann, 2016), but also children’s (Hill et al., 2015) and adults’ books (Gerlach and Font-Clos, 2020). All data included in them could be plausibly encountered by children, which provides opportunities to ablate the influence of architecture/training on the learned linguistic knowledge.

For languages other than English, data availability is the greatest problem for the composition of developmentally plausible datasets. Salhan et al. (2024) use only data available from CHILDES for French, German, Japanese, and Chinese models, whereas Prévot et al. (2024) compare models trained on spoken data (child-directed + adult-adult conversations) with models trained on the French Wikipedia. As such, these first forays into more polyglot BabyLMs are still constrained to the child-directed input found in CHILDES and do not extend to the variety of inputs that children are exposed to (Soderstrom, 2007; Gowenlock et al., 2024). Notably, Suozzi et al. (2025) introduce an Italian BabyLM but do not elaborate on their data sources beyond CHILDES.

Linguistic properties The actual linguistic make-up of pre-training corpora and its influence on linguistic performance have only recently begun to receive increased scrutiny. Focusing on the lexical level, Yam and Paek (2024) measure sentence-level textual complexity with readability metrics based on text-wide word/syllable–sentence ratios for different corpora (CHILDES only, BabyLM corpus, synthetic data, Project Gutenberg). They find that models trained on more complex text perform better at syntactic benchmarks, but simpler data

(CHILDES) is learned better in terms of perplexity and loss convergence. Also on the lexical level, Muckatira et al. (2024) filter regular, non-BabyLM pre-training corpora for text spans that only contain vocabulary also found in English CHILDES data and find that simplified models generate more coherent text than models trained on more complex data and also succeed in syntactic tests if the test data is filtered accordingly. In contrast, Edman et al. (2024) change the semantic content of the pre-training data and use datasets that approximate linguistic input that second-language learners get, e.g., dictionary entries, grammar books, and paraphrased sentences. While grammar books moderately improve syntactic evaluation, there is no positive effect observable for the addition of the other text types.

Filtered corpora While actual research on the structural/syntactic properties of the input is still rather sparse, training on filtered corpora has been used in pilot studies. Patil et al. (2024) and Misra and Mahowald (2024) filter out specific grammatical constructions from the standard BabyLM corpora and then probe the resulting models for knowledge of these grammatical constructions (which might also be analogically learned from related constructions or constructed from their parts). Patil et al. (2024) show that their models succeed on the BLiMP benchmark (Warstadt et al., 2020), even if sentences containing structures targeted in BLiMP’s minimal pair sets are removed. Similarly, Misra and Mahowald (2024) show that acceptability scores for the English AANN construction can be reliably estimated from models that have never seen this specific construction. In sum, then, models appear to be able to generalize from indirect evidence and learn language in a somewhat constructivist, bottom-up fashion.

So far, previous work in NLP has failed to adequately investigate the structural composition of child-directed data. Most studies focus on lexical or semantic properties, emphasizing content over structure, and child-directed data is usually equated with a somewhat fitting vocabulary or with just being authentic data. However, findings from usage-based linguistics suggest that structural properties, like utterance-level construction distributions, play a crucial role in language acquisition. Patil et al. (2024) and Misra and Mahowald (2024) remove specific constructions from their data, whereas we aim to explore whether different global distribu-

Dataset	Description	# Words
CHILDES (MacWhinney, 2000)	Child-directed speech	3,626,301
OpenSubtitles (Lison and Tiedemann, 2016)	Child speech	1,511,144
CallHome (Karins et al., 1997)	Movie subtitles	1,543,094
Klexikon	Phone conversations	176,313
MiniKlexikon	Children’s online encyclopedia	1,384,891
Wikibooks Wikijunior	Simplified online encyclopedia	272,886
Fluter	Educational books	226,773
Project Gutenberg	German youth magazine	2,862,278
Dreambank (Domhoff and Schneider, 2008)	Literature (children’s and young adult)	2,476,133
Leipzig corpus news texts (Goldhahn et al., 2012)	Dream reports	939,197
	Short news texts	1,541,803
<i>Total</i>		16,560,813

Table 1: Lexical token counts for all subcorpora of our corpus

tions of constructions influence the resulting linguistic knowledge and learning trajectories.

4 A German BabyLM dataset

To construct a German dataset, we use a variety of developmentally plausible sources, similar to the English BabyLM data (Warstadt et al., 2023; Choshen et al., 2024). We use i) all data from German CHILDES corpora (MacWhinney, 2000), including frog stories from TalkBank (Berman and Slobin, 1994) and math lessons from ClassBank (Stigler et al., 2000), ii) subtitles from OpenSubtitles (Lison and Tiedemann, 2016), iii) adult conversations from the CallHome corpus (Karins et al., 1997), and iv) written data from Project Gutenberg, from which we downloaded a manually curated sample of children’s books, young adult literature and literature commonly read in German schools. We supply this data with two corpora, the DreamBank database of self-reported dreams (Domhoff and Schneider, 2008) and short news texts from the Leipzig corpus (Goldhahn et al., 2012), although they are not child-directed per se, these sources are child-available in everyday language.

To approximate child-available input even better, we tap into freely available child/learner-directed sources and compile four additional subcorpora for our dataset. The Wikibooks Wikijunior shelf features educational resources aimed at children, focusing on a diverse array of topics such as technology or nature. The Klexikon is a children’s wiki in German, featuring more than 3,000 articles aimed at children between 5–15. A simplified version of it is the MiniKlexikon, which features over 1,500 articles aimed at beginning readers. Finally, we also scrape the complete archives of *Fluter*, a magazine aimed at young adults published by the Federal Agency for Civic Education, which con-

tains a large body of non-fiction. All resources are CC-licensed. Table 1 shows the raw token numbers for all corpora. In sum, we get 16.5M lexical tokens. Before further analysis, we extensively clean and normalize our data (details in Appendix C). We share our dataset on huggingface.

5 Construction distribution analysis

As there are no findings for the distribution of utterance-level construction in German, we conduct our own analysis using spacy. We first split larger paragraphs into individual sentences with the included sender and then annotate these with POS and dependency information. This information serves as the base of our construction annotation procedure. We devise standard construction categories in line with comparable efforts for English (Cameron-Faulkner et al., 2003; Cameron-Faulkner and Noble, 2013; Bunzeck and Diessel, 2024), and use the spacy-annotated data to assign one of the following categories to each utterance:

- **FRA** – utterances that do not contain a verb
- **QWH** – wh-question (introduced by interrogative pronouns)
- **QYN** – yes/no-question (introduced by verbs/auxiliaries)
- **COP** – subject-predicate utterance where the predicate is a copula verb (a form of *sein* or *werden*)
- **IMP** – utterances introduced by verbs in imperative mood
- **SPI** – standard subject-predicate utterance (intransitive verb with no direct/accusative object)
- **SPT** – standard subject-predicate utterance (transitive verb with direct/accusative object)
- **COM** – utterances with two or more lexical verbs

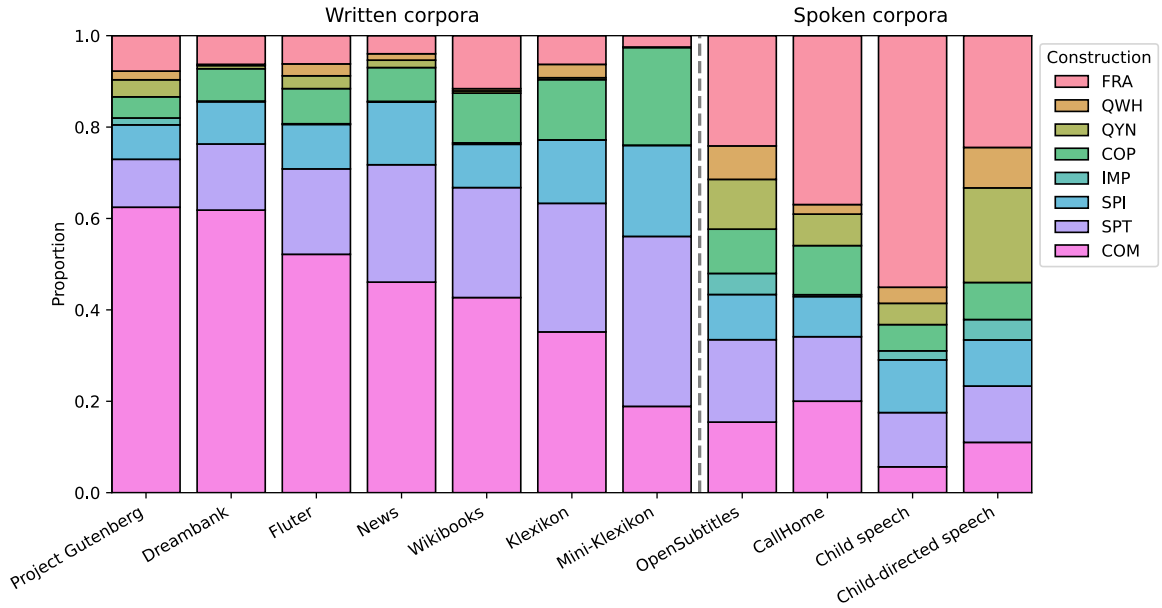


Figure 1: Proportions of utterance-level constructions for all subcorpora in our corpus

This holistic taxonomy is applicable to every utterance across our subcorpora. Against a manually annotated sample of 1,000 sentences, which we balanced for individual subcorpora, our classifier reaches an accuracy of approx. 95%.

Figure 1 visualizes the results of this corpus annotation process, exact proportions are reproduced in Appendix D. Generally, our results confirm earlier findings (Cameron-Faulkner et al., 2003; Cameron-Faulkner and Hickey, 2011; Cameron-Faulkner and Noble, 2013; Bunzeck and Diesel, 2024): Just like English CDS, German CDS features more questions than any other corpus, abounds with fragments, and contains comparatively few complex utterances. The Project Gutenberg data, on the other hand, is characterized by over 60% complex sentences. Interestingly, the construction distribution forms a continuum across our subcorpora. The MiniKlexikon, for example, contains considerably less complex sentences than the other written genres, but over half of its utterances are (in)transitive, canonical SV-sentences. This shows that even these particular sub-genres of child-directed linguistic input feature highly varied and specific constructional profiles that differ from each other.

6 Training data composition

We compose three different corpora of 5M words: i) one corpus maximally resembling the construction composition of child-directed speech (cds), ii) one corpus containing a drastically higher amount of

complex sentences, mirroring the distribution in the Project Gutenberg data (pjpg), and iii) a corpus that is averaged between these two (mix). The relative distributions of construction types can be found in Table 2.

Construction	cds	mix	pjpg
FRA	25%	16.5%	8%
QWH	9%	5.5%	2%
QYN	21%	12.5%	4%
COP	8%	6.5%	5%
IMP	5%	3.5%	2%
SPI	10%	9%	8%
SPT	12%	11%	10%
COM	10%	35.5%	61%

Table 2: Construction proportions of our training sets

Crucially, we sample the individual utterances for our training sets from all subcorpora in our German BabyLM dataset (cf. Table 1). By doing so, we approximate a similar (if not completely equal) mixture of sources and, therefore also a similar mixture of registers, semantic content, etc. This enables us to isolate the effect of construction distributions in our model’s training data, without any interference from the possible differences between the subcorpora.

7 Model training and evaluation

We train small Llama models (Touvron et al., 2023) with transformers (Wolf et al., 2020). To account for the effect of subword tokenization, we compare character-level (3.7M parameters) and subword models (7.7M parameters) for the three datasets. We train all models for one epoch (loss

		Character			Subword		
		cds	mix	pjg	cds	mix	pjg
Word-level	Lexical decision	97.4%	97.6%	97.4%	84.6%	81.9%	80.8%
	Surprisal	99.8%	99.8%	99.9%	91.5%	90.3%	90.1%
	AntiSurprisal	99.3%	98.9%	99.7%	76.5%	75.4%	75.4%
Syntax	Simple Agreement	90%	90%	95.7%	80%	84.3%	92.1%
	Across a Prepositional Phrase	61.5%	65.5%	61.8%	74.8%	73.5%	75.5%
	Across a Subject Relative Clause	67.1%	66%	62.4%	78.4%	73.7%	97.9%
	Short Verb Phrase Coordination	69.8%	68.8%	67.9%	82.6%	93.5%	99.5%
	Long Verb Phrase Coordination	53.6%	60.6%	63%	60.6%	78.8%	78%
	Across Object Relative Clause	58.6%	54.2%	53%	64%	66.7%	81.6%
	Within Object Relative Clause	59.8%	56.4%	72.5%	55.8%	55.7%	49.9%
Semantics	XCOMPS	51.5%	49.1%	49.1%	51.4%	52%	52.3%

Table 3: Final evaluation results (accuracies) for all benchmarks

curves and hyperparameters are in Appendix E) and share them on the huggingface model hub ([LINK REMOVED]). To test the effect of different random initializations and our sampling strategy, we reproduce pre-training for the cds models (see Appendix F).

In line with current best practices to linguistic probing, we use minimal pair probing datasets to evaluate our LMs’ linguistic knowledge in German. The datasets always consist of a correct/grammatical and a matched incorrect/ungrammatical string. We use minicons (Misra, 2022) to score the sentences. We evaluate 19 model checkpoints (10 for the first 10% of training, 9 for the remaining 90%).

Word-level probing To gauge lexical knowledge, we adapt the experimental setup from Bunzeck et al. (2025): We use wuggy (Keuleers and Brysbaert, 2010) to generate 1,000 nonce words (e.g. *promsen*) from existing words (e.g. *bremsen*) and then evaluate how surprised the models are by i) the words with the context of a prepended white space (lexical decision, Le Godais et al., 2017), ii) the words in a plausible context sequence (surprisal, Hale, 2001), and iii) the words randomly inserted into implausible contexts (antisurprisal, Shafabadi and Wisniewski, 2025). If the model is less surprised by the existing word, we count this as a correct choice in our paradigm. We calculate accuracies over the whole dataset.

Syntactic probing For syntactic probing, we use the CLAMS dataset (Mueller et al., 2020), which contains syntactic minimal pairs (grammatical/ungrammatical) for German (e.g. *Die Autoren lachen/*lacht.*). The included seven phenomena all revolve around subject-verb agreement in different contexts (across PPs, relative clauses, with

coordination, etc.), resulting in different degrees of difficulty. We score the sentences for their likelihood. We calculate accuracies for correctly rated pairs (grammatical sentence more likely) over the whole dataset.

Semantic probing To evaluate our models’ semantic knowledge, we use the XCOMPS dataset (He et al., 2025). It contains conceptual minimal pairs (e.g. *Garnele hat einen Kopf./*Ein Bikini hat einen Kopf.*)¹ that test whether LMs have acquired knowledge about conceptual properties of real-world entities. Again, we score the sentences for their likelihood and calculate accuracies for correctly rated pairs over the whole dataset.

8 Results

8.1 MP probing

Table 3 shows model-wise accuracies for all minimal pair sets after training for one epoch. For the word-level evaluations, accuracy scores are generally high. Across all tasks, the character models perform with almost perfect accuracy. No effect of the constructional composition of the training data is identifiable here. For the subword models, this is not true. Here, the model trained on more questions/fragments and less complex utterances (cds) outperforms the model that approximates written language on the construction level (pjg). The improvements range from 1% for anti-surprisal to 2-3% on lexical decision.

For the syntactic tests, the picture is more nuanced. Generally speaking, all our models learn to distinguish grammatical and ungrammatical sen-

¹We sample 1,000 MPs with randomized replacement, as the other conditions contain implausible/wrong minimal pairs. Furthermore, the quality of translation is not optimal, as exemplified by the missing determiner in front of *Garnele*.

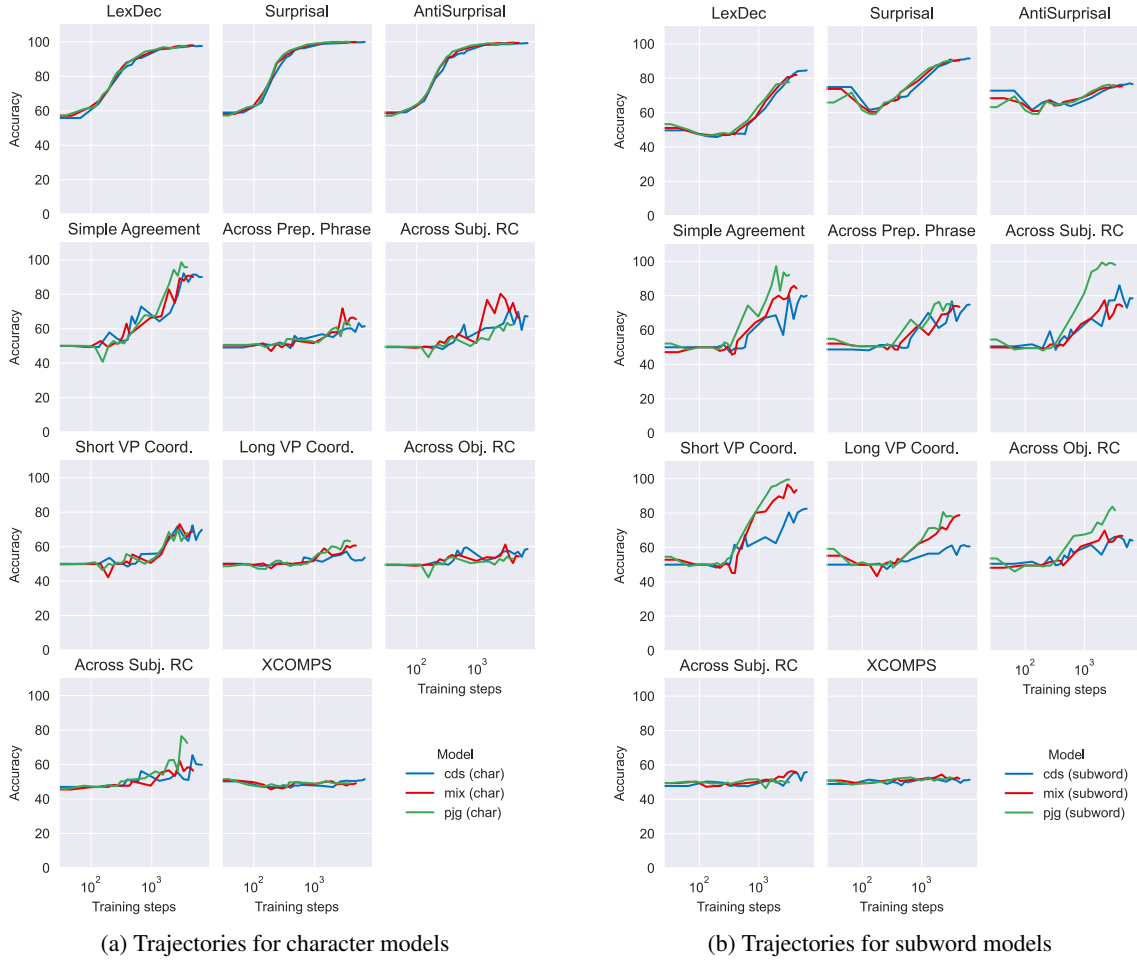


Figure 2: Learning trajectories for all minimal pair benchmarks

tences with agreement phenomena. The best scores are achieved on more simplistic phenomena like simple agreement or coordination with short verb phrases. Agreement phenomena that involve longer dependencies and distracting nouns, e.g. within and across relative clauses, are the hardest to learn. For the character models, the cds model outperforms the others on three out of seven tests, including both “across subj./obj. relative clause” conditions. For three other tests, the pjg model wins out, whereas the mix model achieves the highest scores on only one test (agreement across prepositional phrases). The subword models show a somewhat different picture. Here, the pjg model wins in five categories, whereas cds and mix achieve best scores in one each.

The evaluation scores for the XCOMPS benchmark reveal that our small models do not reliably learn the conceptual knowledge underlying the included minimal pairs. Scores revolve around the chance baseline, with subword models performing slightly better than character models for 2/3 data

mixtures. However, these scores are also not much worse than those reported in the XCOMPS paper (e.g. 56–69% for Llama 3.1), so more research is needed to establish ways of robust and appropriate probing of semantic knowledge in small LMs.

8.2 Learning trajectories

Figure 2 shows the learning trajectories of our models across one training epoch. In line with best practices in ML (Viering and Loog, 2023), we log-scale the x-axis in our plots. This allows us to also trace early learning in more detail.

For our character models, word-level learning happens rapidly in an s-shaped curve. No differences are visible between the datasets, performance improvements align almost perfectly. For the subword models, the learning processes are not as nicely monotonically improving. Rather, the learning trajectories show a dip early in training, which then later on recovers to fairly good accuracy scores. Interestingly, despite differences in final scores, the improvements across models

trained on quite different datasets still align with regard to turning and takeoff points.

This pattern is also confirmed by the learning trajectories for the syntactic phenomena. While the pjj models trained on more complex utterances frequently reach the highest final scores, it is remarkable to see how the improvements for all models seem to happen in parallel. The global shape of the trajectory is the same for all syntactic tests, regardless of the construction distribution. For example, the learning curve for simple agreement is steeper for the pjj models once learning has started, but take-off points are neatly aligned. These take-off points are pushed back by the individual paradigms' complexities – simple agreement and short VP coordination begin to improve earlier than MPs containing RCs. Finally, it is interesting to note that for the character models, word-level learning consistently stabilizes before syntactic learning, whereas both processes seem to happen concurrently in subword models (mirroring findings for English reported by [Bunzeck and Zarriß, 2025](#)).

9 Discussion and conclusion

This paper set out to investigate whether the constructional profile of CDS, which is shaped in a way to support the acquisition of *functional* language competence, is actually conducive to *formal* language learning, or whether its relative lack of complex sentences and canonical SV(X) utterances makes it so impoverished that meaningful formal learning does not happen. The results of our utterance-level corpus analysis for German align with earlier findings on CDS and book language for English ([Cameron-Faulkner et al., 2003](#); [Cameron-Faulkner and Noble, 2013](#); [Bunzeck and Diessel, 2024](#)) and Irish ([Cameron-Faulkner and Hickey, 2011](#)), adding to the growing evidence that this linguistic distribution is fairly universal, at least in WEIRD societies ([Henrich, 2024](#)).

The results of our language modeling experiments are much more surprising. The constructional profile of training data is not overly important for training small, developmentally plausible LMs from scratch. Rather, starting/turning points of the resulting learning trajectories are mostly determined by the respective amount of training steps. Despite models trained with more complex input resulting in slightly better performance, they do not begin to learn earlier. Global learning trajec-

tories are extremely similar, only the local magnitude differs between different constructional setups. For word-level learning processes such as lexical decision or (anti)surprisal tests, data with more fragments and questions even seems to be rather conducive, whereas models trained on more complex utterances do not learn this level of knowledge equally well.

What does this now mean for theories of language acquisition? On a formal level, there seems to be no disadvantage for models trained on allegedly less “complex” or somewhat impoverished data. Despite more complex data leading to slightly better benchmark scores, the learning trajectories remain largely unaffected. What really shapes the learning process is the amount of input, not its formal complexity (similar to findings for children by [Huttenlocher et al., 1991](#); [Rowe, 2012](#)). An increase in appropriate construction types for child-rearing and functional language learning (like questions, imperatives, or fragments) does not hinder formal learning (if only reduce its magnitude slightly). Conversely, it even enables word-level learning to converge to a better end state. This also aligns with a broader trend found in language acquisition studies — the complexity and quality of input can indeed predict later language skills ([Noble et al., 2020](#); [Alroqi et al., 2023](#)), but the ground level is always extremely high already: being a competent user of the language itself. Furthermore, quality varies with many more extralinguistic factors like the number of siblings ([Laing and Bergelson, 2024](#)) or cultural factors ([Bergelson et al., 2023](#); [Bunce et al., 2024](#)).

Finally, our findings also add to the growing body of research on BabyLMs ([Warstadt et al., 2023](#); [Hu et al., 2024](#)). Similarly to English models, our German BabyLMs only need little data – the cds dataset contains approx. 820,000 sentences, and given the estimation by [Cameron-Faulkner et al. \(2003\)](#) that children hear around 7,000 utterances per day, our data approximates the number of utterances heard over only 120 days – to learn a fair amount of syntax and almost impeccable lexical knowledge, with trajectories mirroring those of English models ([Bunzeck and Zarriß, 2025](#)). We hope that our dataset enables other scholars to carry out experiments with developmentally plausible LMs beyond the dominating English LMs, and that our data sources provide inspiration to those compiling BabyLM corpora for their own languages of interest.

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