Complexity dynamics in child-adult dialogue: local adaptation and language learning

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Abstract

In this work, we use corpus-based data-driven methods to study the effects of adaptation and alignment on two children's language learning process, as quantified by an increase in their linguistic complexity over time. We explore turn-based adaptation in complexity, and we analyse how these local dynamics change across dialogues over longitudinal time. We find that adults adapt to child complexity, though local adaptation diminishes as the children grow older. We also employ a general linear model to investigate whether increased child complexity can be predicted by lexical, syntactic and semantic alignment measures, beyond the effects of both age and adult complexity. Our results suggest that adaptation and syntactic alignment might benefit the language learning process, as adults adapt locally to child language use.

1 Introduction

In their first few years of life, children develop from being completely linguistically passive into being active dialogue participants. Typically, children start producing their first meaningful words when they are around a year old, and subsequently start combining them together into increasingly complex sentences between the ages of two and three (Hoff, 2013). By the age of five, more abstract and complex conversations are possible, for example about the various animals likely to chase cats (Figure 1). Indeed, children do not learn language in isolation: they are surrounded by competent language users, with whom they also interact. Adults, in turn, modify their language use when addressing children. Cross-culturally, child-directed speech tends to have specific features, such as higher pitch and more contrastive intonational contours (Fernald et al., 1989), that make it particularly attractive for children (ManyBabies Consortium, 2020).

MOT: and what's this ? CHI: a kitty . MOT: kitty . CHI: my little kitty . MOT: your little kitty . MOT: where's the kitty ? CHI: kitty gone .	CHI: sometimes the kitten chases the cat . ROG: sometimes the kitten chases the cat . CHI: sometimes . ROG: sometimes but not always . CHI: a lot of times dogs chases cats .

Figure 1: Child-adult dialogue excerpts. Sarah (`CHI`) discusses cats at the ages of 2;3 (left) and 5;1 (right).

The adaptation of language use to a conversational partner is a well-known phenomenon in studies of human dialogue: during discourse, dialogue partners may for example line up in their use of prosody, but also in their semantic conceptualization, syntactic structures and word choices. One factor argued to drive such linguistic alignment is that it helps to achieve communicative goals: mutual understanding is more likely when interlocutors design their utterances to be understandable for each other (Clark, 1996). In child-adult dialogue, it is presumably the adult who is more skilled at adapting their speech to their interlocutor's needs (Street and Cappella, 1989). But how do adults decide what the child's communicative needs are?

In order to communicate successfully with children, an important factor for adults to consider would be the child's linguistic competence, which gradually increases as the child grows older. The so-called *finetuning hypothesis* posits that child-directed speech is a dynamic type of linguistic behaviour that develops throughout the child's language learning process (Snow, 1995, 1972). In the weak version of this hypothesis, adaptation to the child happens on a global level: adults choose a degree of linguistic complexity based on the overall development of the child. Under the strong version of the finetuning hypothesis, the modified degree of complexity is instead viewed as a result of local adaptation: adults contingently adjust their utterances in response to the child's linguistic behaviour in ongoing dialogue.

Next to being helpful for communication, adults' finetuning to the child's language level is additionally suggested to support the language learning process (Bruner, 1985). Parallel research has shown that both the content and frequency of child-directed speech may aid important components of language acquisition, like the recognition of linguistic units and vocabulary building (Nelson et al., 1989; Kuhl et al., 1997; Weisleder and Fernald, 2013). But specifically adults' alignment to the child may provide additional advantages for the child's linguistic development. Especially for word learning, language that is optimized for communication (i.e. well-aligned between speakers) is also beneficial for learning: children can more easily infer word meanings from an informative and coordinated conversational context (Frank and Goodman, 2014; Yurovsky, 2018). However, the communicative benefit of alignment may not be the same for all linguistic dimensions: although a lack of semantic alignment can quickly result in communicative failure, syntactic errors usually do not (Brown and Henlon, 1970; Newport et al., 1977). Moreover, only hearing simpler and less variable syntactic structures may actually make it harder for children to learn more complex ones (Montag et al., 2015; Montag and MacDonald, 2015). Hence, there could be meaningful contrasts in the effects of alignment on learning for different levels of linguistic analysis.

In this project we contribute to the existing work using a corpus-based investigation into the language acquisition process of two North-American children learning English. Our research questions are as follows: (1) Do adults adapt locally to children in linguistic complexity, and does their degree of adaptation change over time? (2) Do local semantic, lexical and syntactic alignment patterns predict an increase in the child's produced linguistic complexity, beyond the effect of age? We find that adults adapt to child linguistic complexity on the level of turns, but also that the degree of this local adaptation decreases as children grow older. Additionally, we find some indication for positive effects of alignment patterns on learning.

2 Related work

Early corpus research considering the finetuning hypothesis was conducted by Sokolov (1993). Analyzing differences and repetitions between adjacent child-adult utterances, he found a contingent relationship that depended on both lexical class and child age. This finding indicates the presence of local adaptation of adult to child language, and is hence in line with the strong version of the finetuning hypothesis. Nevertheless, it also shows that finetuning may be developmentally sensitive: the relationship between child and adult utterances changed over time.

Kunert et al. (2011) investigated adaptation in child-adult dialogue by computing correlations between complexity metrics for different levels of linguistic analysis. They show that linguistic complexity is correlated between child and adult utterances, and that some correlations still hold when controlling for age. Kunert et al. argue that their results support the strong version of the finetuning hypothesis. However, their complexity metrics were computed at the dialogue level, and they did not include any direct measurements of turn-based local adaptation.

Dale and Spivey (2006) introduce recurrence analysis to look more closely into local interactional patterns, and demonstrate that utterances between children and caregivers are coordinated on the syntactic level, especially early in development. Fernández and Grimm (2014) expand their metrics to examine local convergence in lexical, syntactic and semantic patterns, and show that distance between turns has a significant effect on recurrence rates. These studies successfully expose alignment patterns in child-adult dialogue at the level of turns, but they did not investigate the development of such patterns over longitudinal time or their effects on learning.

More recently, Yurovsky et al. (2016) studied alignment in child-adult dialogue over development, and show that parental alignment to the child decreases over time. In addition, Denby and Jurovsky (2019) find that the degree of parental alignment significantly predicts vocabulary development independent of other demographic features. These findings support the developmentally sensitive version of the finetuning hypothesis posited by Sokolov (1993), and also indicate promising effects of alignment on learning. However, both Yurovsky et al.'s and Denby and Jurovsky's measures of alignment are based only on function words, and learning is measured through scores on vocabulary tests. Hence, the potentially varying effects of different types of alignment on language learning more generally remain to be explored.

In this project, we quantify language learning as an increase in produced linguistic complexity over development. We first assess turn-based adaptation in complexity, and explore how these local dynamics change across dialogues and as the child grows older. Then, we test whether increased complexity of child utterances can be predicted by measures of lexical, syntactic and semantic recurrence beyond the effects of age and adult complexity.

3 Methods

3.1 Corpus & preprocessing

Our data is drawn from the Brown corpus (Brown, 1973) in the CHILDES database (MacWhinney, 2000). This corpus contains transcripts of child-adult dialogues over a few years of the children's development. We selected all dialogue transcripts from the children Sarah (age range 2;6 – 5;1) and Adam (2;3 – 5;2)[1]. Like Fernández and Grimm (2014), we consider a turn to be a stretch of speech by one speaker, which may include more than one utterance[2]. We further extract *turn pairs* between the adult and child in both directions: with adult utterances first (`ADT-CHI` pair) and with child utterances first (`CHI-ADT` pair), and we maintain the original order of adjacent pairs in the dialogue.

3.2 Metrics

3.2.1 Turn-based complexity metrics

We use the following turn-based quantifications to measure complexity across different linguistic dimensions (inspired by Kunert et al. (2011)'s dialogue-based measures):

Mean Utterance Length (MUL): mean length of utterances (in words) averaged over the turn, roughly indicating *syntactic complexity*.

Mean Word Length (MWL): mean length of words (in characters) averaged over the turn, roughly indicating *morphological complexity*.

Mean Number of Word Types (MWT): mean number of distinct word types (POS tags) per utterance averaged over the turn, roughly indicating *morphosyntactic complexity*.

[1]All data and analysis code, as well as additional plots can be found in our repository: `https://github.com/mdhk/CDM-project`.

[2]When adults other than the child's parent (e.g. the investigators) took part in the dialogue, we considered them all as coming from the same 'adult' speaker, though we maintained the original turn structure (i.e. subsequent utterances from different adult speakers were not considered a single turn).

Mean Number of Unique Words (MUW): mean number of distinct words per utterance averaged over the turn, roughly indicating *lexical complexity*.

Mean Number of Consonant Triples (MCT): mean number of orthographic consonant triples per utterance averaged over the turn, roughly indicating *phonological complexity*.

Mean Turn Length (MTL): mean number of utterances per turn, roughly indicating *discourse complexity*.

3.2.2 Recurrence-based metrics

To quantify local alignment between dialogue participants, we compute recurrence rates for lexical, syntactical and semantic measures. In order to compute recurrence rates, we create recurrence matrices (based on Fernández and Grimm, 2014), as visualized in Figure 2. In these matrices, child turns (y-axis) are plotted against the adult turns (x-axis), and cells with a darker shade indicate a higher degree of alignment. If local alignment takes place, darker shades are expected around the matrix diagonal (i.e. directly adjacent turns). The local recurrence rate can then be quantified for varying distances d as the mean recurrence over all cells within a distance d from the diagonal. In order to derive to what extent recurrence stems from local, turn-by-turn interactions, we also compute recurrence rates over matrices with randomly shuffled turns. In Figure 3 we plot how recurrence rates are affected by different distances d, and how this compares with shuffled control dialogues. We can observe a divergence between normal and shuffled dialogues for lower values of d, which suggests that recurrence values are affected by temporal structure. We compute the recurrence rates using a turn distance of $d = 2$. This value allows us to capture the temporal structure of a dialogue, whilst also taking into account non-adjacent turns. For each final metric, we subtract the recurrence rate as computed for shuffled dialogues: the resulting difference should thus reflect the recurrence as occurring from strictly local interactions. Inspired by Fernández and Grimm (2014), we calculate recurrence rates using the following alignment measures:

Semantic Alignment: We aim to measure semantic alignment by computing the cosine simi-

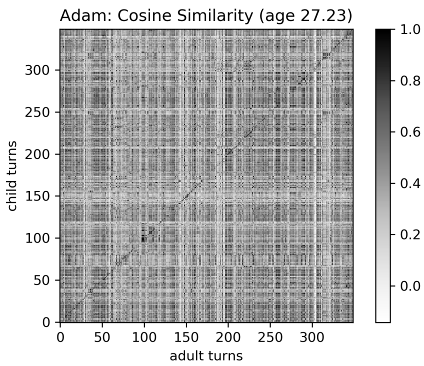

Figure 2: Adam: Cross-recurrence plot for semantic alignment.

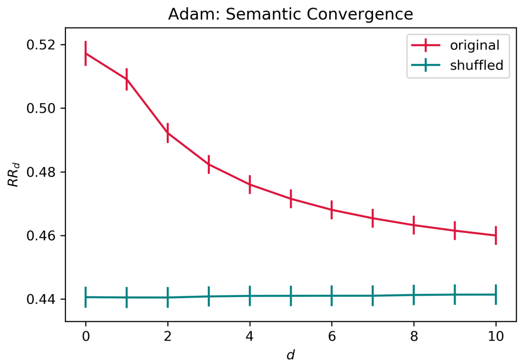

Figure 3: Adam: Recurrence rates for different distances d, on normal and shuffled dialogues.

larity between vector representations of turns, for each pair of turns. Vector representations of turns are obtained by embedding turns with a pre-trained instance of the BERT language model (Devlin et al., 2019). To this end, we use the Python `sentence-transformers` library.

Syntactic Alignment: We measure syntactic alignment as the proportion of bigrams that are shared between adjacent utterances: the number of n-grams that are present in both utterances, divided by the number of n-grams in the longer utterance.

Lexical Alignment: This metric is computed similarly to *Syntactic Alignment*, though here we only consider shared lexeme unigrams.

3.3 Description of analyses

3.3.1 Local and global adaptation in complexity

To explore the local and global adaptation in linguistic complexity between the adult and the child, we compute the six complexity measures described above (MUL, MWL, MWT, MUW, MCT, MTL) on each turn-pair in every dialogue. For this research question, we are primarily focused on the adult's adaptation to the child.

Local Adaptation: To quantify the local adaptation between the adult and the child, we compute the Pearson correlation coefficient on the turn-based metric results for a given dialogue. A dialogue's Pearson correlation coefficient indicates the extent to which the second participant in the turn pair adapts to their dialogue partner across all turns in the dialogue. After performing this computation on all dialogues, we plot the correlation scores over time and fit the data using least squares regression. This plot and corresponding slope provide an indication of how local adaptation changes over time for this metric. When examining the adult's adaptation to the child, we use complexity metrics computed on turn pairs where the child speaks first (and vice versa).

Global Adaptation: To understand the change in child and adult linguistic complexity as the child develops, we also compute the six complexity metrics per dialogue over time. For a given complexity metric, computed per turn, we take the mean across all turns in a dialogue to calculate a dialogue-based complexity measure. We plot the computed mean complexity across time for both the child and adult. We also compute the least squares regressions on this data. For the adult, these global complexity results serve as an indicator of linguistic adaptation towards the child over time. For the child, we consider only those global complexity measures that increase significantly over time for both children as measures of language learning. Additionally, as a direct measure of correlation at the dialogue-level, without accounting for time, we replicate the scatter plots from in Kunert et al. (2011), which display the mean complexity metric values for each dialogue in the dataset for the child and adult.

3.3.2 Measuring effects on language learning

We use General Linear Models (GLMs) to measure the effects of alignment, local and global adaptation on language learning. GLMs are fitted with the `glm()` method from the R `stats` package[3]. We aim to measure language learning through a proxy of increasing child complexity, where a higher child complexity is understood to

[3]We used R version: 3.6.1

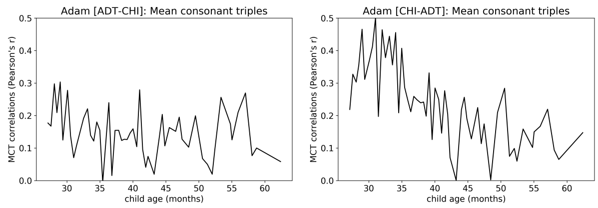

Figure 4: Adam: MCT Pearson correlations over time

reflect greater linguistic ability. For a given dialogue, the child complexity (CHI_CP) is computed as the z-transformed sum of turn-based metrics MWT, MUW and MUL. The choice for these metrics specifically is motivated by their relationship with age, which was found to have a significant positive effect on all of these metrics, for both children. An overview of the effects of age on all complexity metrics can be found in Table 4 in the Appendix. We apply a z-transform standardization to each metric prior to summing, to ensure appropriate comparability between metrics. For fitting the GLMs, we employ as predictor variables the *adult complexity* (ADT_CP), which is computed similarly to the child complexity, and recurrence metrics PosBi, LexUni, LexBi and Semantic.

4 Results

4.1 Local and global adaptation in complexity

Local Adaptation: Figure 4 displays the Pearson correlation coefficient for each dialogue over time for the mean consonant triples metric. The plot on the left was created from turn pairs where the adult speaks first and thus represents the child's adaptation to the adult. Similarly, the plot on the right represents the adult's local adaptation to the child. The plot on the left shows a relatively flat trend in the level of the child's local adaptation over time, with scores in the range of 0.0 to 0.3. The plot on the right initially shows considerably higher correlation scores compared to the child adaptation plot (up to approximately 0.5) and a decreasing trend in correlation scores over time. This indicates that the adult has higher levels of turn-based adaptation while the child is younger and that this level of adaptation decreases over time. Table 1 displays the regression data representing the change in local adaptation over time for all metrics for both directions of turn pairs from the Adam corpus. We observe a small, but significant, decreasing trend in both child and adult local adaptation for several

Adult Adaptation			
	Slope	Intercept	Sign.
MWT	-0.001	0.138	
MCT	-0.009	0.609	***
MTL	-0.001	0.027	
MWL	-0.006	0.405	***
MUL	-0.002	0.186	*
MUW	-0.002	0.160	*

Child Adaptation			
	Slope	Intercept	Sign.
MWT	-0.002	0.118	**
MCT	-0.002	0.217	
MTL	0.000	-0.023	
MWL	-0.001	0.164	
MUL	-0.003	0.156	***
MUW	-0.003	0.144	***

Table 1: Adam: Estimated regressions for change in child's and adult's local adaptation over time (least-squares regressions on Pearson's r scores). Significance levels *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

of the metrics. The largest change we observe is for the adult's adaptation in MWL and MCT over time. The corresponding regression data for Sarah can be found in Table 3, where we observe similar trends for the child and less pronounced changes in local adaptation for the adult.

Change in Global Complexity: Figure 5 contains six plots each displaying a mean complexity measure over all dialogues in the Adam corpus. Table 4 contains the corresponding regression data for Adam and Sarah. The following metrics produce a significant increase in child complexity over time for Adam: MUL, MWT, MUW, and MCT. The increases in complexity for these metrics can be observed in the figure. The plots for MWL and MTL do not display the same trend in increased complexity. For Sarah, the complexity metrics which display a significant increase in child complexity over time are MUL, MWL, MWT, and MUW.

As an indication of the adult's global adaptation over time, we also analyze the change in adult complexity across dialogues. The adult complexity remains relatively flat for all metrics for both Adam and Sarah. This result can be observed visually in Figure 5 as well as numerically in Table 4 for both the Adam and Sarah datasets.

Plot 6 displays the MUL for all dialogues (left) and for a single dialogue (right). The Pearson's r for the global plot is approximately 0.67 and for the right plot is approximately 0.14. Each point on the global plot represents a dialogue such as the one shown here on the right. In the global plot for MUL we see a positive correlation between the child and adult for this metric. In the local plot, we see little variation in MUL scores.

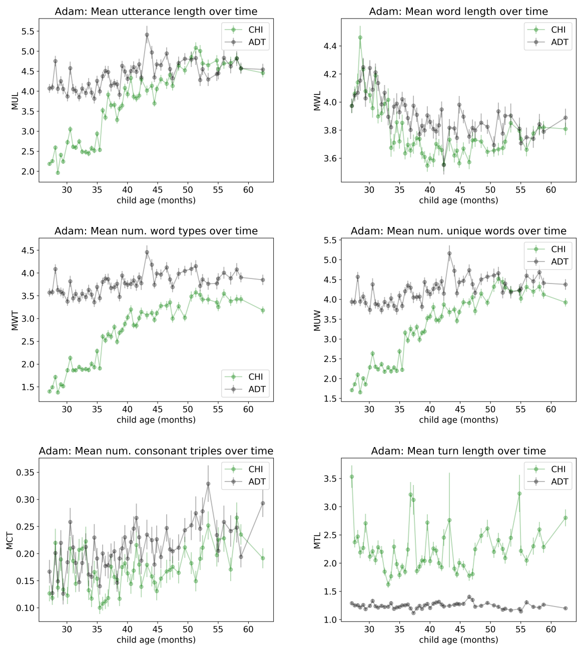

Figure 5: Adam: Mean complexity measures over time

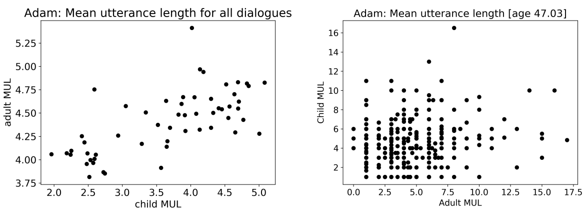

Figure 6: Child vs. Adult MUL in the Adam dataset, over all dialogues (left) and within one dialogue (right). Each datapoint in the left plot reflects one dialogue; each datapoint in the right plot reflects one pair of adjacent turns.

4.2 Effects of alignment on language learning

Results of the GLM fits for both Adam and Sarah are given in Table 2. We assess how well child linguistic complexity at the dialogue level (`CHI_CP`) is predicted by child age, all three recurrence measures (`Semantic`, `Syntactic` and `Lexical` alignment), and adult complexity (`ADT_CP`) at the dialogue level, as well as by the interactions of all measures with child age.

As expected, we find a significant effect of age on complexity for both children: general linguistic complexity (as measured by the z-transformed sum of MWT, MUW and MUL) increases as the children grow older. Also for both children, we find that adult complexity has a significant positive effect on child complexity at the dialogue level: both children used more complex language in those dialogues where adults also used more complex language. For Adam, we find that his linguistic complexity is significantly predicted by the degree of syntactic recurrence: in dialogues where adults and Adam aligned more on the syntactic level, Adam produced more complex utterances. For both the effects of adult complexity (in both children) and syntactic alignment (in Adam), we find a significant negative interaction with age: the effects of these measures on child complexity *decrease* as the children get older. For both children, we find no significant effect of either semantic or lexical alignment, nor their interactions with age, on the child's produced linguistic complexity.

5 Discussion

We analyzed the general development of linguistic complexity over several years in the language acquisition process of two North-American children learning English. For both children, we find that their complexity significantly changes over time in all examined linguistic levels of analysis, except for discourse complexity (mean turn lengths). Metrics showing a stable significantly increasing trend for both children are the mean utterance length (MUL, syntactic complexity), mean number of unique

Predictors	Adam	Sarah
`(Intercept)`	-10.79 ***	-10.60 ***
`Age`	0.277 ***	0.246 ***
`Semantic`	-0.636	0.145
`Syntactic`	1.967 *	0.266
`Lexical`	-2.398	-0.327
`ADT_CP`	0.864 **	0.451 *
`Age:Semantic`	0.013	-0.007
`Age:Syntactic`	-0.052 *	-0.009
`Age:Lexical`	0.067	0.002
`Age:ADT_CP`	-0.017 *	-0.010 *

Table 2: Beta coefficients for Adam and Sarah after fitting a GLM model for `CHI_CP`; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Overall deviance in `CHI_CP` captured by the models (adjusted D^2): 0.895 for Adam and 0.770 for Sarah.

word types (MWT, morphosyntactic complexity) and mean number of unique words (MUW, lexical complexity). Hence, we interpreted the increases in these metrics as representative indicators of the language learning process. Some metrics instead showed a significant decrease over time, which may in fact provide equally valid clues about learning. For example, the decrease in Adam's mean word length over time (Table 4) could be a result of an increasing use of function words. However, since these trends were not present in both children, we only used the increasing MUL, MWT and MUW metrics as a proxy for learning in our later analyses – further research is needed to determine the exact long-term dynamics between different complexity metrics over language development.

We also find a stable increase of adult linguistic complexity over time for the same three metrics (MWT, MUW and MUL; Table 4): as children grow older, adults start using more complex language to them. This is in line with the weak version of the finetuning hypothesis, indicating that adults globally adapt to the child's general developmental level. However, we also find evidence for local adaptation of adults to child language use: turn-based linguistic complexity is correlated between adjacent child and adult utterances within dialogues. We computed these correlations for both child responses to adult utterances and for adult responses to child utterances. Here, we found that stronger correlations in general in the latter, indicating that adults adapt more to child language than the other way around. For several measures (MUL, MWL, MUW and MCT) we found a decreasing trend in the correlations over time: as children grow older, adults adapt less. This is in line with previous results supporting a developmentally sensitive version of the finetuning hypothesis (Sokolov, 1993; Yurovsky et al., 2016; Denby and Jurovsky, 2019): adults locally adapt to the child's linguistic behaviour to optimize communication, but the degree of local adaptation decreases as children become more communicatively competent themselves.

Our second analysis aimed to investigate the effects of local alignment patterns across several linguistic dimensions on the long-term language learning process. Here, we aggregated the MUL, MWT and MUL measures into a general complexity measure. We then explored to what extent the general complexity of child utterances can be predicted by the complexity of adult utterances as well as three alignment measures, beyond the positive effect of age. We found that child complexity is significantly predicted by adult complexity on the dialogue level for both children, indicating that adult and child linguistic complexity is generally aligned across dialogues. We separately assessed the effects of semantic, lexical and syntactic alignment. Surprisingly, we found no effect of either lexical or semantic alignment on learning, as we might have expected based on earlier results for word learning (Frank and Goodman, 2014; Denby and Jurovsky, 2019). Our general measure of language learning is intended to capture an increase in produced lexical and (morpho)syntactic complexity, rather than the development of vocabulary. This might partially account for the lack of an effect of semantic alignment on learning, if this reported effect indeed primarily influences the learning of vocabulary. We did find a positive effect of syntactic alignment on produced complexity in one of the two children: Adam produced more complex utterances in dialogues where syntactic structures were more aligned between his utterances and those of adults. Syntactic alignment was measured as the proportion of shared P between adjacent turns. Considering this, further analysis on this finding would be required to examine how much of this type of alignment is accounted for by direct repetitions (for example as a result of corrective feedback; Hiller and Fernández, 2016), especially since earlier results indicated that direct repetitions accounted for at least some of the adult-child adaptation in linguistic complexity (Kunert et al., 2011).

Additionally, since we only find the effect of syntactic alignment in one out of two children, further work is needed to explore individual differences in the influence of local alignment on language learning. Finally, we found a significant interaction with age for both significantly positive effects on child complexity: as children grow older, the effects of adult complexity and syntactic alignment decrease. These results provide additional support for developmentally sensitive local finetuning, in line with both our first analysis and earlier work.

6 Conclusion

Alignment between dialogue participants is a well-known phenomenon in human conversation: potentially driven by communicative goals, interlocutors align to eachother in their language use across many linguistic dimensions. In child-adult dialogue, adults' alignment to children's language use may additionally support children's language learning process. We found evidence that adults indeed locally adapt to child complexity levels for several linguistic measures, but also that the degree of this adaptation decreases over time: adults finetune less as children's own communicative abilities grow. Additionally, we found some indications that adaptation in general complexity and alignment in syntactic structures positively affect language learning. We conclude that in the two datasets we analyzed, adults adapted locally to child language use, which may have not only benefited communication, but also the children's learning process.

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References

Roger Brown. 1973. *A first language: The early stages*. Harvard U. Press.

Roger Brown and Henlon. 1970. Derivational complexity and order of acquisition in child speech. In John R. Hayes, editor, *Cognition and the Development of Language*, pages 11–53. Wiley, New York.

Jerome Bruner. 1985. *Child's Talk: Learning to Use Language*. W. W. Norton & Company, New York.

Herbert H. Clark. 1996. *Using Language*. Cambridge University Press, Cambridge.

Rick Dale and Michael J. Spivey. 2006. Unraveling the dyad: Using recurrence analysis to explore patterns of syntactic coordination between children and caregivers in conversation. *Language Learning*, 56:391–430.

Joseph Denby and Daniel Jurovsky. 2019. Parents' linguistic alignment predicts children's language development. In *Proceedings of the Annual Meeting of the Cognitive Science Society*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3651–3657.

Anne Fernald, Traute Taeschner, Judy Dunn, Mechthild Papousek, Bénédicte de Boysson-Bardies, and Ikuko Fukui. 1989. A cross-language study of prosodic modifications in mothers' and fathers' speech to preverbal infants. *Journal of Child Language*, 16(3):477–501.

Raquel Fernández and Robert M Grimm. 2014. Quantifying Categorical and Conceptual Convergence in Child-Adult Dialogue. In *Proceedings of the Annual Meeting of the Cognitive Science Society 36*, page 7.

Michael C. Frank and Noah D. Goodman. 2014. Inferring word meanings by assuming that speakers are informative. *Cognitive Psychology*, 75:80–96.

Sarah Hiller and Raquel Fernández. 2016. A Data-driven Investigation of Corrective Feedback on Subject Omission Errors in First Language Acquisition. In *Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning*, pages 105–114. Association for Computational Linguistics.

Erika Hoff. 2013. *Language Development*. Cengage Learning.

Patricia K. Kuhl, Jean E. Andruski, Inna A. Chistovich, Ludmilla A. Chistovich, Elena V. Kozhevnikova, Viktoria L. Ryskina, Elvira I. Stolyarova, Ulla Sundberg, and Francisco Lacerda. 1997. Cross-Language Analysis of Phonetic Units in Language Addressed to Infants. *Science*, 277(5326):684–686.

Richard Kunert, Raquel Fernández, and Willem Zuidema. 2011. Adaptation in child directed speech: Evidence from corpora. In *SemDial 2011: Proceedings of the 15th Workshop on the Semantics and Pragmatics of Dialogue*, pages 112–119.

Brian MacWhinney. 2000. *The CHILDES project: Tools for analyzing talk: Transcription format and programs*. Psychology Press.

ManyBabies Consortium. 2020. Quantifying Sources of Variability in Infancy Research Using the Infant-Directed-Speech Preference. *Advances in Methods and Practices in Psychological Science*, 3(1):24–52.

Jessica L. Montag, Michael N. Jones, and Linda B. Smith. 2015. The Words Children Hear: Picture Books and the Statistics for Language Learning. *Psychological Science*.

Jessica L. Montag and Maryellen C. MacDonald. 2015. Text exposure predicts spoken production of complex sentences in 8- and 12-year-old children and adults. *Journal of Experimental Psychology: General*, 144(2):447–468.

Deborah G. Kemler Nelson, Kathy Hirsh-Pasek, Peter W. Jusczyk, and Kimberly Wright Cassidy. 1989. How the prosodic cues in motherese might assist language learning. *Journal of Child Language*, 16(1):55–68.

Elissa L. Newport, Henry Gleitman, and Lila R. Gleitman. 1977. Mother, Id Rather Do It Myself: Some Effects and Non-Effects of Maternal Speech Style. In Catherine E. Snow and Charles A. Ferguson, editors, *Talking to Children*, pages 109–149. Cambridge University Press.

Catherine E. Snow. 1972. Mothers' Speech to Children Learning Language. *Child Development*, 43(2):549–565.

Catherine E. Snow. 1995. Issues in the Study of Input: Finetuning, Universality, Individual and Developmental Differences, and Necessary Causes. In *The Handbook of Child Language*, pages 180–193. Blackwell.

Jeffrey L. Sokolov. 1993. A local contingency analysis of the fine-tuning hypothesis. *Developmental Pyschology*, 29:1008–1023.

Richard L. Street and Joseph N. Cappella. 1989. Social and linguistic factors influencing adaptation in children's speech. *Journal of Psycholinguistic Research*, 18(5):497–519.

Adriana Weisleder and Anne Fernald. 2013. Talking to Children Matters: Early Language Experience Strengthens Processing and Builds Vocabulary. *Psychological Science*, 24(11):2143–2152.

Daniel Yurovsky. 2018. A communicative approach to early word learning. *New Ideas in Psychology*, 50:73–79.

Daniel Yurovsky, Gabriel Doyle, and Michael C. Frank. 2016. Linguistic input is tuned to children's developmental level. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, pages 2093–2098.

Appendix

Adult Adaptation			
	Slope	Intercept	Sign.
MWT	-0.001	0.086	
MCT	0.000	0.119	
MTL	0.000	-0.017	
MWL	-0.001	0.195	
MUL	-0.002	0.093	*
MUW	-0.002	0.087	*

Child Adaptation			
	Slope	Intercept	Sign.
MWT	-0.001	0.022	
MCT	-0.002	0.165	*
MTL	0.000	-0.030	
MWL	-0.003	0.221	***
MUL	0.001	-0.064	
MUW	0.000	-0.014	

Table 3: Sarah: Estimated regressions for change in child's and adult's local adaptation over time (least-squares regressions on Pearson's r scores). Significance levels *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Adam dataset	**Child**		**Adult**	
Measure	Slope	Sign.	Slope	Sign.
MWT	0.065	***	0.014	***
MCT	0.002	***	0.003	***
MTL	0.004		-0.0004	
MUW	0.083	***	0.019	***
MWL	-0.010	***	-0.009	***
MUL	0.088	***	0.020	***

Sarah dataset	**Child**		**Adult**	
Measure	Slope	Sign.	Slope	Sign.
MWT	0.049	***	0.022	***
MCT	-0.005	***	0.001	
MTL	-0.0009		-0.003	
MUW	0.057	***	0.029	***
MWL	0.008	***	-0.002	
MUL	0.061	***	0.029	***

Table 4: Estimated slopes for change in the children's and adults' produced linguistic complexity over time (least-squares regressions for complexity measures as predicted by child age). Significance levels *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.