Is word segmentation child’s play in all languages?

Georgia R. Loukatou
Laboratoire de Sciences Cognitives et de Psycholinguistique,
Département d’études cognitives, ENS, EHESS, CNRS, PSL University
georgialoukatou@gmail.com

Steven Moran
Damián E. Blasi
Sabine Stoll
University of Zurich

Alejandrina Cristia
Laboratoire de Sciences Cognitives et de Psycholinguistique,
Département d’études cognitives, ENS, EHESS, CNRS, PSL University

Abstract

When learning language, infants need to break down the flow of input speech into minimal word-like units, a process best described as unsupervised bottom-up segmentation. Proposed strategies include several segmentation algorithms, but only cross-linguistically robust algorithms could be plausible candidates for human word learning, since infants have no initial knowledge of the ambient language. We report on the stability in performance of 11 conceptually diverse algorithms on a selection of 8 typologically distinct languages. The results are evidence that some segmentation algorithms are cross-linguistically valid, thus could be considered as potential strategies employed by all infants.

1 Introduction

Six-month-old infants can recognize recurrent words in running speech, even with no meaning available or with experimentally impoverished cues to wordhood (Saffran et al., 1996). Most words do not appear in isolation (Brent and Siskind, 2001), so infants would need to discover the form of words in their caregivers’ input before attaching them to meaning. Since infants do not know which language(s) will be found in their environment at the beginning of development, they would be better off by using segmentation strategies that perform above chance for any language. In fact, despite the fact that languages vary widely in a number of dimensions affecting word segmentation, all human languages are learnable for infants (see Discussion for the question of the extent of variation in human learning).

1.1 Unsupervised bottom-up segmentation across languages

The problem of learners retrieving words in input has a long history in computational approaches (e.g., Harris 1955; Elsner et al. 2013; Lee et al. 2015). Most previous computational research has used as input texts representing phonologized language, that is, sequences of phonemes with no overt word boundaries, and the task is to retrieve these. Several algorithms inspired by laboratory research on infant word segmentation are currently represented in WordSeg, an open source package (Bernard et al., 2018).

Are such algorithms as robust to cross-linguistic variation as human infants are? Some previous work has assessed the generalizability of specific approaches across different languages, typically concluding that strong performance differences arise (Johnson 2008; Daland 2009; Gervain and Erra 2012; Fourtassi et al. 2013; Saksida et al. 2017; Loukatou et al. 2018, with the possible exception of Phillips and Pearl 2014a,b).

However, very little previous research compares the performance of a wide range of algorithms using diverse and cognitively plausible segmentation methods within a large set of typologically diverse languages and closely matched corpora, with unified coding criteria for linguistic units.

1.2 The present work

In this paper, we sought to fill this gap by employing a systematic approach that samples both over the space of algorithms and the space of human languages. We used 11 segmentation algorithms included in WordSeg, for improved reproducibility and transparency.

As for languages, we used the ACQDIV
Table 1: Number of children, sentences and word tokens for each language corpus. “m.syn.” stands for morphological synthesis derived from sto: A language received a “high” here if nominal and verbal complexity were both listed as the highest in that work; and low if they were both in the lowest levels, and moderate otherwise. “ % s.com.” stands for syllable complexity, measured as average percentage of vowels per total phonemes for each word. Languages are represented by the first three letters of their names.

| lang | #chi | #sent | #words | m.syn. | %s.com. |
|------|------|-------|--------|--------|---------|
| Inu  | 4    | 13,166| 22,045 | high   | 57      |
| Chi  | 6    | 160,524| 459,585| high   | 50      |
| Tur  | 8    | 249,507| 875,349| high   | 44      |
| Rus  | 5    | 468,397| 1,302,650| med.   | 43      |
| Yuc  | 3    | 29,795 | 88,018 | med.   | 51      |
| Ses  | 4    | 23,539 | 62,024 | low    | 55      |
| Ind  | 10   | 399,606| 1,179,505| low    | 46      |
| Jap  | 7    | 242,774| 741,594 | low    | 51      |

Inu
database (Moran et al., 2016), which contains a set of typologically diverse languages, as explained in Stoll and Bickel (2013). All corpora were gathered longitudinally and were ecologically valid, with transcriptions of child-directed and child-surrounding speech recordings (target children’s age ranges from 6 months to 6 years).

ACQDIV contains data for eight languages with large enough data sets to allow for analyses of the type used here: Chintang (Stoll et al., 2015), Indonesian (Gil and Tadmor, 2007), Inuktitut (Allen, 1996, Unpublished), Japanese (Miyata, 2012b, a; Oshima-Takane et al., 1995; Miyata, 1992), Russian (Stoll, 2001; Stoll and Meyer, 2008), Sesotho (Demuth, 1992, 2015), Turkish (Küntay et al., Unpublished), and Yucatec Mayan (Pfeiler, Unpublished).

The present study addresses the following questions:

1. **Do algorithms perform above chance level for all languages?** Algorithms that systematically perform at or below chance level would not be plausible strategies for infants.

2. **Is the rank ordering of algorithm performance similar across languages?** That is, is the case that the same algorithms perform poorly or well across languages? If unsupervised word discovery algorithms pick up on general linguistic properties that are stable across this typologically diverse sample, then we expect the rank ordering to be rather stable. If, conversely, some algorithms pick up on cues that are useful in one language but noxious in another, then the rank ordering may change.

## 2 Methods

Phonemization was done using grapheme-to-phoneme rewrite rules adapted to each language (Moran and Cysouw, 2018). Only adult-produced speech was included.

The input to each algorithm was the phonemized transcript, with word boundaries removed. Sentence boundaries were preserved because infants are sensitive to them from before 6 months of age (Christophe et al., 2001; Shukla et al., 2011). Table 1 gives the number of children, sentences, and words across corpora, as well as a rough metric of morphological and phonological complexity.

For lack of space, we will only briefly describe the algorithms drawn from WordSeg (see Johnson and Goldwater 2009; Monaghan and Christiansen 2010; Lignos 2012; Daland and Zuraw 2013; Sakaida et al. 2017; Bernard et al. 2018). All algorithms were used with their default parameters.

Baseline algorithms represent the simplest segmentation strategies possible. The first baseline, $p=0$, is a learner who treats each whole sentence as a unit, cutting at 0% of possible points. The second baseline is a learner (innately) informed about average word duration, cutting at a probability level of average word length. Since in the reduced lexicon expected for child-surrounding speech, words average 6 phonemes in length in several languages (Shoemark et al., 2016), $p=1/6$ was used.

The Diphone Based Segmentation algorithm (DiBS) is based on phonotactics, and implements the idea that phoneme sequences that span phrase boundaries also span word breaks (Daland and Pierrehumbert, 2011; Daland, 2009). The learner decides whether there is a boundary in the middle of a bigram sequence if the probability of the sequence with a word boundary is higher than the probability without the boundary.

Other algorithms are also based on the idea that sequences with lower statistical coherence tend to span word breaks, but use backwards or forwards transitional probabilities (BTP and FTP respectively; in a sequence $xy$, BTP is the frequency of $xy$ divided by the frequency of $y$; FTP by the frequency of $x$) or mutual information (MI). MI is defined as the log base 2 of the frequency of
Table 2: Number of languages performing above baseline \( p=0 \) and \( p=1/6 \). Columns show the mean, the lowest and highest percentage of correctly segmented word tokens for each algorithm and the corresponding language. Languages are represented by the first three letters of their names. “PUD” stands for PUDDLE. “Base0” and “Base6” stand for baseline \( p=0 \) and \( p=1/6 \).

| algo | Base0 | Base6 | | mean | | min | | max |
|------|-------|-------|-------|-------|-------|-------|-------|
| AG   | 6/8   | 7/8   | 37    | 7     | Rus   | 65    | Ind   |
| DiBS | 8/8   | 8/8   | 30    | 25    | Jap   | 41    | Inu   |
| FTPa | 7/8   | 8/8   | 28    | 17    | Inu   | 36    | Ind   |
| Mlr  | 7/8   | 7/8   | 27    | 7     | Inu   | 36    | Ind   |
| FTPr | 7/8   | 7/8   | 25    | 11    | Inu   | 30    | Rus   |
| PUD  | 6/8   | 6/8   | 22    | 7     | Ind   | 34    | Ses   |
| BTPa | 6/8   | 6/8   | 17    | 10    | Ses   | 27    | Ind   |
| Mla  | 7/8   | 8/8   | 17    | 15    | Jap   | 25    | Inu   |
| BTPr | 6/8   | 5/8   | 14    | 9     | Inu   | 22    | Yuc   |

Table 2: Number of languages performing above baseline \( p=0 \) and \( p=1/6 \). Columns show the mean, the lowest and highest percentage of correctly segmented word tokens for each algorithm and the corresponding language. Languages are represented by the first three letters of their names. “PUD” stands for PUDDLE. “Base0” and “Base6” stand for baseline \( p=0 \) and \( p=1/6 \).

Table 3: Mean percentage of correctly segmented word tokens for each language. Languages are listed in rough order of morphological complexity (see Table 1). Columns show the mean, lowest and highest percentage of correctly segmented word tokens per language, and the corresponding algorithm. “PUD” stands for PUDDLE.

| lang | mean | min | max |
|------|------|-----|-----|
| Inuktitut | 17 | 7 | Mr |
| Chintang | 25 | 9 | BTPr |
| Turkish | 25 | 14 | PUD |
| Russian | 22 | 7 | AG |
| Yucatec | 27 | 16 | Mla |
| Sesotho | 24 | 9 | BTPr |
| Indonesian | 29 | 7 | PUD |
| Japanese | 26 | 14 | BTPa |

3 Results

Results are shown in Tables 2 (reporting on algorithms) and 3 (reporting on languages). Next, we address our research questions.

1. Do algorithms perform above chance level for all languages? If chance is defined as the highest of the two baselines (\( p=0, 1/6 \)), 1 algorithm performed above chance in all 8 languages (DiBS). However, if we relax this criterion, AG, FTPa, FTPr, Mlr and Mla also performed above chance for nearly all languages. No algorithm performed below chance level for more than half of the languages.

2. Is the rank ordering of algorithm performance similar across languages? Figure 1 illustrates the correlation of performance order for algorithms across languages. Spearman correlations (median= .38) suggested that there is a similar rank ordering

\[ xy \div \text{product of frequency of } x \text{ and that of } y; \text{ the version in WordSeg draws from Saksida’s implementation (Saksida et al., 2017). Whether to add a word boundary or not depends on a threshold, which can be based on a local comparison (relative, where one cuts if the TP or MI is lower than that for neighboring sequences); or a global comparison (absolute, where one cuts if the transition is lower than the average of all TP or MI over the sum of different phoneme bigrams). It should be noted that previous authors originally implemented TPs on syllables (Saksida et al., 2017; Gervain and Erra, 2012), but here the basic units are phonemes. Combining all of the above yields 6 versions, namely FTPr, FTPa, BTPr, BTPa, Mlr and Mla. Johnson and Goldwater (2009) elaborated on adaptor grammars (AG), which are ideal approximations to the segmentation problem. They assume that learners create a lexicon of minimal, recombilable units found in their experience. AG uses the Pitman-Yor process, a stochastic process of probability distribution which prefers the reuse of frequently occurring rules versus creating new ones to build a lexicon, then uses this lexicon to parse the input. This process is conceptually related to Zipf’s Law (Zipf, 1935) and leads to realistic word frequency distributions.

Finally, Phonotactics from Utterances Determine Distributional Lexical Elements (PUDDLE) is an incremental alternative algorithm (Monaghan and Christiansen, 2010), where learners build a lexicon by entering every utterance that cannot be broken down further, and using such entries to find subparts in subsequent utterances.

WordSeg was used both for segmentation and evaluation. Each algorithm returns their input with spaces where the system hypothesizes a break. Evaluation is done with reference to orthographic word boundaries. Scripts used for corpus preprocessing and segmentation as well as results and supplementary material are available at https://osf.io/6q5e3/.
of algorithm performance across languages. Inuktitut and Russian were the only languages not following the general ordering.

The models’ detailed performance, measured in percentage of correctly segmented word tokens, can be found in the online supplementary material and in this paper’s Appendix. An error analysis would be beyond the scope of this paper. However, three categories of incorrect cases have been measured and can be found online. This analysis documents cases of oversegmentation (words split up in their components), undersegmentation (two or more words segmented as one) and missegmentation (all other errors).

4 Discussion

First, no algorithm performed systematically below chance level in our study. However, we cannot say that they all performed above chance for all languages either. This is mainly due to the good results in baseline p–0, especially salient for morphologically complex languages such as Inuktitut. This is expected, since in this language a substantial number of sentences are composed by a single word (which morphologically encodes what in other languages would be expressed syntactically by using several words).

Second, there was some stability in the order of performance for algorithms across this set of diverse languages, suggesting that these unsupervised word discovery algorithms pick up on general linguistic properties that are stable across our sample, and not language-dependent cues that could potentially not work for some languages.

In this distinct performance ranking, some algorithms were systematically above chance and among the first in order of performance. These include DiBS and AG, combining both desiderata of cross-linguistic stability and high segmentation performance. DiBS, the one algorithm in our sample applying a phonotactics strategy, was robust across languages and not strongly affected by the differences found across these languages in morphology and phonological complexity (counter previous conclusions based on English versus Korean, Daland and Zuraw 2013). DiBS implements an optimal boundary setting based on the Bayes’ theorem and co-occurrence statistics. Thus, our results support previous experimental findings that infants may use such tools to acquire language.

Our study is the first to explore segmentation differences across both multiple algorithms and multiple languages. We therefore are in a position to compare segmentation performance differences across these two. We found that differences in average performance across algorithms (min=14 for BTPr, max= 37 for AG, 23% points) were larger than differences in performance across languages (min=17 for Inuktitut, max=24 for Indonesian, 7% points). This indicates that variation across languages was comparatively small.

Also, average percentage of correctly segmented words for the more morphologically complex languages (Chintang, Inuktitut and Turkish) was 19%, only 3% lower than average percentage for the simpler languages in our sample (Japanese, Sesotho and Indonesian). This is striking evidence that in this set of diverse languages, intrinsic differences in language structure may not be large enough to create particular difficulties in segmentation.

To sum up, this study provides evidence that, if infants do anything similar to one or more of the algorithms proposed in previous natural language processing research and investigated here, then they would be well-equipped to get a head start in segmenting word-like units regardless of what their native language is. Experimental evidence suggests slight variation in the timing of acquisition of different linguistic features, as a function
of factors such as the transparency of forms, and the complexity of paradigms (e.g., Slobin 1985). Given the small differences found across our unsupervised word segmentation algorithms, such variation might come from something else, such as meaning acquisition, which would require algorithms different from the ones we explored here.

Before closing, we would like to acknowledge some limitations of this work. Defining words can be obscure (Daland, 2009) and there is no cross-linguistically valid general definition of ‘word’ (Haspelmath, 2011). Consequently, it would make sense to also evaluate unsupervised segmentation algorithms using morpheme edges and at other definitions of wordhood (Bickel and Zúñiga, 2018). For this, we would need appropriately annotated data sets, which are currently missing. What is worse, not every language lends itself to simple definitions: Some languages in ACQDIV lack morpheme segmentation simply because this is not feasible in that language.

In this paper, we focus on correctly segmented words. An error analysis would not be easily interpretable, because not all corpora have morpheme annotations. For example, when documenting oversegmentation errors, we would not be able to distinguish between reasonable cases where words are split up into meaningful, morpheme-like components, and other cases. Similarly, in an undersegmentation analysis, we would not be able to focus on collocations. Future work is invited to study in more detail such errors in the algorithms’ performance.

Finally, computational models can be informative proofs of principle, but nothing assures us they truly represent what infants are doing. To this end, laboratory experiments (Johnson and Jusczyk, 2001) and the study of natural variation (Slobin, 1985) are irreplaceable, even if challenging to perform, particularly at a large scale and sampling from many different cultures.

Acknowledgments

AC acknowledges funding from the Agence Nationale de la Recherche (ANR-17-CE28-0007 LangAge, ANR-16-DATA-0004 ACLEW, ANR-14-CE30-0003 MechELex, ANR-17-EURE-0017); and the J. S. McDonnell Foundation Understanding Human Cognition Scholar Award. This research was enabled by the European Union’s Seventh Framework Program (FP7/2007–2013) under grant agreement 615988 (PI Sabine Stoll).

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**Appendix**

The models’ performance, measured in percentage of correctly segmented word tokens, can be found in Table 4.

| algo | AG | DiBS | FTPa | Mfr | FTr | PUD | BTPa | Mla | BTP | Base0 | Base6 |
|------|----|------|------|-----|-----|-----|------|-----|-----|-------|-------|
| Inu  | 20 | 41   | 17   | 7   | 11  | 8   | 14   | 25  | 9   | 35    | 16    |
| Chi  | 36 | 33   | 30   | 32  | 12  | 19  | 12   | 17  | 11  | 6     | 8     |
| Rus  | 42 | 33   | 29   | 33  | 27  | 14  | 19   | 23  | 9   | 12    | 12    |
| Yuc  | 7  | 33   | 29   | 29  | 33  | 17  | 19   | 23  | 9   | 9     | 7     |
| Ses  | 48 | 28   | 30   | 31  | 14  | 28  | 17   | 15  | 8   | 11    | 12    |
| Ind  | 39 | 31   | 25   | 31  | 28  | 30  | 32   | 22  | 9   | 9     | 8     |
| Jap  | 65 | 30   | 27   | 30  | 25  | 34  | 29   | 32  | 11  | 9     | 12    |
|  | 43 | 28   | 28   | 29  | 28  | 34  | 29   | 30  | 11  | 12    | 13    |

Table 4: Percentage of correctly segmented word tokens for each language and algorithm. Languages are listed in rough order of morphological complexity (see Table 1). “PUD” stands for PUDDLE. “Base0” and “Base6” stand for baseline p=0 and p=1/6. Languages are represented by the first three letters of their names.