Unsupervised Word Segmentation in Context

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Abstract

This paper extends existing word segmentation models to take non-linguistic context into account. It improves the token F-score of a top performing segmentation models by 2.5% on a 27k utterances dataset. We posit that word segmentation is easier in-context because the learner is not trying to access irrelevant lexical items. We use topics from a Latent Dirichlet Allocation model as a proxy for “activities” contexts, to label the Providence corpus. We present Adaptor Grammar models that use these context labels, and we study their performance with and without context annotations at test time.

1 Introduction and Previous Works

Segmentation of the speech stream into lexical units plays a central role in early language acquisition. Because words are generally not uttered in isolation, one of the first task for infants learning a language is to extract the words that make up the utterances they hear. Experimental research has shown that infants are able to segment fluent speech into word-like units within the first year of life (Jusczyk and Aslin, 1995). How does this ability emerge? There is evidence that infants use a broad array of linguistic cues to perform word segmentation (e.g., phonotactics (Jusczyk et al., 1993a), prosodic information (Jusczyk et al., 1993b), statistical regularities (Saffran et al., 1996)). Past experimental and modeling research on speech segmentation has mainly focused on linguistic cues, treating them as independent from other non-linguistic cues naturally occurring in the child learning environment. Yet, language appears in context and is constrained by the events occurring in the daily life of the child. For example, during an eating event one is most likely to speak about food, while during a zoo-visit event, people are more likely to talk about the animals they see. Activity contexts may provide a natural structure to speech that would be readily be accessible to children. A recent study using dense recordings of a single child’s language development (Roy et al., 2006) showed that words appearing in specific activity contexts are learned faster (Roy et al., 2012). Relatedly, Johnson et al. (2010) showed that Adaptor Grammars (AGs) performed better on a segmentation task when the model has access to a hand-annotated set of objects present in the environment, that it can use to learn simultaneously word-object associations (see also (Frank et al., 2009)). This supports the view that integrating multiple sources of information, linguistic and non-linguistic, can improve learning.

Following this idea, we posit that information from the broader context in which a word has been uttered may simplify the learning problem faced by the child. In particular, our hypothesis postulates that speech segmentation is easier when using vocabularies that are related to a specific activity (eating, eating, eating). This work is licensed under a Creative Commons Attribution 4.0 International Licence. Page numbers and proceedings footer are added by the organisers. Licence details: http://creativecommons.org/licenses/by/4.0/
Table 1: Most probable words in the 7 final topics

<table>
<thead>
<tr>
<th>egg</th>
<th>apple</th>
<th>book</th>
<th>banana</th>
<th>milk</th>
<th>butter</th>
</tr>
</thead>
<tbody>
<tr>
<td>ball</td>
<td>shape</td>
<td>cat</td>
<td>fire</td>
<td>fish</td>
<td>triangle</td>
</tr>
<tr>
<td>truck</td>
<td>car</td>
<td>name</td>
<td>school</td>
<td>piece</td>
<td>train</td>
</tr>
<tr>
<td>color</td>
<td>bear</td>
<td>battery</td>
<td>minute</td>
<td>hair</td>
<td>phone</td>
</tr>
<tr>
<td>block</td>
<td>phone</td>
<td>minute</td>
<td>minute</td>
<td>minute</td>
<td>minute</td>
</tr>
</tbody>
</table>

≈ food  ≈ shapes  ≈ playing  ≈ toys  ≈ time  ≈ drawing  “garbage”

To evaluate this hypothesis, we applied topic modeling (Blei et al., 2003) to automatically derive activity contexts on a corpus of child directed speech, the Providence corpus (Demuth et al., 2006), and tested the influence of such topics on a word segmentation task extending the AG models used in (Börschinger et al., 2012). We found that a model augmented with the assumption that words are dependent upon the topic of the discourse (as a proxy for activity context) performs better than the same model without access to the discourse topic. This suggests that the broader context in which sentences are uttered may help in the word segmentation process, and could presumably be used at various stages of language development.

The paper is structured as follows. Section 2 presents a novel approach to augment a corpus with contextual annotations derived from topic models. Section 3 quickly explains Adaptor Grammars, the framework that we used to express all our models. Section 4 presents all the models that were used in the results. Section 5 describes the Providence corpus and the experimental setup. Section 6 shows our quantitative and qualitative results. Finally, we discuss the implications for models of language learning.

2 Topics as Proxies for Contexts

Roy et al. (2012) found high correlations between human-annotated activity contexts and topics from a latent Dirichlet allocation model (LDA) (Blei et al., 2003), thus showing that using topics as proxies for contexts is a sound approach. Topic modeling infers a topic distribution for each “document” (a bag of words) in the corpus. Since “documents” were not annotated in our corpus, we developed the following 3-step approach to automatically segment it into documents.

Firstly, for all the children of the Providence corpus, we used recording sessions as hard document boundaries. We considered as a “possible document” every contiguous sequence of sentences separated by at least 10 seconds of silence, according to the orthographic transcript. We also identified “possible documents” using cues such as “bye/hi”, indicating a change of participants. This segmentation resulted in an over-segmented corpus (compared to context switches), yielding a total of 16,742 documents.

Secondly, we used the gensim software (Rehůřek and Sojka, 2010) to train a topic model (LDA), and get the topic distributions for each of these documents. We used the symmetric KL-divergence to measure the distance between two topic distributions before and after a “possible document” boundary. If the distance was above a threshold, we considered this boundary as a document boundary. Otherwise we merged both “possible documents” through this silence. The threshold was set empirically to discriminate between two topic distributions that correspond to different activity contexts. After this step, we assume that each of the resulting 8,634 documents maps to an activity context.

Thirdly, we applied LDA again on this new segmentation to get the topic distribution, hence the activity context, of each document. The number of topics is qualitatively chosen to correspond to the number of main activity contexts (eating / playing / drawing / etc.) that occur in the Providence dataset (we used 7 topics), the resulting most topic specific words are shown in Table 1. Finally, for each document, we got a distribution on topics, and we annotated the document with the most probable topic. By doing that, we throw away graded information about the distribution on topics for each document. We could make use of the full distribution, but here we are only interested in the most probable topic as a proxy for activity context. We do not posit that the infants learn the topic models on linguistic cues while bootstrapping speech and segmentation, but rather that they get activity context from non-linguistic cues.

We did LDA only on nouns (as they contain most of the semantics), weighted by TF-IDF.
3 Adaptor Grammars

Adaptor Grammars (Johnson et al., 2007) are an extension of probabilistic context-free grammars (PCFGs) that learn probability of entire subtrees as well as probabilities of rules. A PCFG \((N, W, R, S, \theta)\) consists of a start symbol \(S\), \(N\) and \(W\) disjoint sets of nonterminals and terminal symbols respectively, \(R\) is a set of rules producing elements of \(N\) or \(W\). Finally, \(\theta\) is a set of distributions over the rules \(R\). An AG \((N, W, R, S, \theta, A, C)\) extends the above PCFG with a subset \((A \subseteq N)\) of adapted nonterminals, each of them \((X \in A)\) having an associated adaptor \((C_X \in C)\). An AG defines a distribution over trees \(G_X, \forall X \in N \cup W\). If \(X \not\in A\), then \(G_X\) is defined exactly as for a PCFG:

\[
G_X = \sum_{X \rightarrow Y_1 \ldots Y_n \in R_X} \theta_X \rightarrow Y_1 \ldots Y_n TD_X(G Y_1 \ldots G Y_n)
\]

With \(TD_X(G_1 \ldots G_n)\) the distribution over trees with root node \(X\) and each subtree \(t_i \sim G_i\) i.i.d. If \(X \in A\), then there is an additional indirection (composition) with the distribution \(H_X\):

\[
G_X = \sum_{X \rightarrow Y_1 \ldots Y_n \in R_X} \theta_X \rightarrow Y_1 \ldots Y_n TD_X(H Y_1 \ldots H Y_n)
H_X \sim C_X(G_X)
\]

We used \(C_X\) adaptors following the Pitman-Yor process (PYP) (Perman et al., 1992; Teh, 2006) with parameters \(a\) and \(b\). The PYP generates (Zipfian) type frequencies that are similar to those that occur in natural language (Goldwater et al., 2011). Metaphorically, if there are \(n\) customers and \(m\) tables, the \(n+1\)th customer is assigned to table \(z_{n+1}\) according to (\(\delta_k\) is the Kronecker delta function):

\[
z_{n+1}|z_1 \ldots z_n \sim \frac{ma + b}{n + b} \delta_{m+1} + \sum_{k=1}^{m} \frac{nk - a}{n + b} \delta_k
\]

For an AG, this means that adapted non-terminals \((X \in A)\) either expand to a previously generated subtree \((T(X)_k)\) with probability proportional to how often it was visited \((n_k)\), or to a new subtree \((T(X)_{m+1})\) generated through the PCFG with probability proportional to \(ma + b\).

4 Word segmentation models

4.1 Unigram model

This most basic model just generates words as sequences of phonemes. As \(Word\) is underlined, it means it is adapted, and thus we learn a “word unit-like” vocabulary. \(Phon\) is a nonterminal that expands to all the phonemes of the language under consideration.

\[
Sentence \rightarrow Word^+
Word \rightarrow Phon^+
\]

where :

\[
Word^+ \Leftrightarrow \{ Words \rightarrow Word \} \cup \{ Words \rightarrow Word Words \}
\]

4.2 Collocations and Syllabification

The baseline that we are using is commonly called the “colloc-syl” model (Johnson, 2008; Börschinger et al., 2012) and is reported at 78% token F-score on the standard Brent version of the Bernstein-Ratner corpus. It posits that sentences are collocations of words, and words are composed of syllables. (Goldwater et al., 2009) showed how an assumption of independence between words (a unigram model) led to under-segmentation. So, above the \(Word\) level, we take the collocations (co-occurring sequences) of words into account.
Furthermore, there is evidence that 8-month-old infants track syllable frequencies (Saffran et al., 1996), and the “colloc-syll” model can take that into account. Word splits into general syllables and initial- or final- specific syllables. Syllables consist of onsets or codas (producing consonants), and nuclei (vowels). Onsets, nuclei and codas are adapted, thus allowing this model to memorize sequences or consonants or sequences of vowels, dependent on their position in the word. Consonants and vowels are the pre-terminals, their derivation is specified in the grammar into phonemes of the language.

\[
\begin{align*}
\text{Sentence} & \rightarrow \text{Colloc}^+ \\
\text{Colloc} & \rightarrow \text{Word}^+ \\
\text{Word} & \rightarrow \text{StructSyll}
\end{align*}
\]

For notations purposes, all this syllabification is appended after Word by Word → StructSyll. All details about the collocations and syllabification grammars can be found in (Johnson, 2008). Here is an example of a (good) parse of “yuwanttusid6buk” with this model, skipping the StructSyll derivations:

```
Sentence
  Colloc  Colloc  Colloc
    Word    Word    Word
      yu     want   tu
```

4.3 Including topics (contexts)
Parentheses denote that these terms are optionals, and “|” denotes “or”. Both Word\textsubscript{tK} and Word are adapted, but this time on the same level of hierarchy. This model allows the use of both topic-specific and common words in sentences, and it learns \#topics + 1 vocabularies. We call this model with common.

An example of a correct parse with this model is given by:

```
Sentence
  \_t3
  Colloc
    Word
    Word
    Word
  Colloc_t3
    Word_t3
    Word_t3
    Word_t3

```

5 Experimental setup

The Providence corpus (Demuth et al., 2006) consists of audio and video, weekly or bi-weekly, recordings of 6 monolingual English-speaking children home interactions. Each recording is approximately 1 hour long. This corpus spans approximately from their first to third year. We used the whole corpus to extract the topics to get more stable and general activity contexts. For all the following results, we used only the Naima portion between 11 months and 24 months, consisting in 26,425 utterances (sentences) and 135,389 tokens (words). The input consist in DARPA-BET-encoded sequences of phonemes with about 4200 word-types in the Naima subset. We followed the same preparation procedure as in (Börschinger et al., 2012), where more details about the corpus can be found.

We used the last version of Mark Johnson’s Adaptor Grammars software\textsuperscript{2}. All the additional code (preparation, topics, grammars, learning) to reproduce these experiments and results is freely available online\textsuperscript{3}, along with the datasets annotations derived from topic modeling\textsuperscript{4}. For the adaptors, we used a \textit{Beta}(1,1) (uniform) prior on the PY P \textit{a} parameter, and a sparse \textit{Gamma}(100, 0.01) prior on the PY P \textit{b} parameter. We ran 500 iterations (finishing at \(\approx 0.05\%\) of log posterior variation between the last 2 iterations) with several runs for each subset of the Naima dataset.

6 Results

6.1 Unsupervised words segmentation

Table 2: Mean (token and boundary) F-scores (f), precisions (p), and recalls (r) for different models depending on the size of dataset (age range).

<table>
<thead>
<tr>
<th>months</th>
<th>baseline</th>
<th>share vocab</th>
<th>split vocab</th>
<th>with common</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>token</td>
<td>f</td>
<td>p</td>
<td>r</td>
</tr>
<tr>
<td>11-12</td>
<td>.80</td>
<td>.79</td>
<td>.81</td>
<td>.77</td>
</tr>
<tr>
<td>11-15</td>
<td>.81</td>
<td>.81</td>
<td>.82</td>
<td>.76</td>
</tr>
<tr>
<td>11-19</td>
<td>.82</td>
<td>.82</td>
<td>.83</td>
<td>.77</td>
</tr>
<tr>
<td>11-22</td>
<td>.81</td>
<td>.82</td>
<td>.81</td>
<td>.77</td>
</tr>
<tr>
<td></td>
<td>boundary</td>
<td>f</td>
<td>p</td>
<td>r</td>
</tr>
<tr>
<td>11-12</td>
<td>.90</td>
<td>.88</td>
<td>.91</td>
<td>.88</td>
</tr>
<tr>
<td>11-15</td>
<td>.91</td>
<td>.91</td>
<td>.92</td>
<td>.89</td>
</tr>
<tr>
<td>11-19</td>
<td>.92</td>
<td>.92</td>
<td>.93</td>
<td>.90</td>
</tr>
<tr>
<td>11-22</td>
<td>.92</td>
<td>.93</td>
<td>.91</td>
<td>.90</td>
</tr>
</tbody>
</table>

The key metric of interest is the token F-score (harmonic mean of precision and recall of words). Table 2 gives all the scores for an increasingly large dataset (as in (Börschinger et al., 2012)). Figure 1 shows the month-by-month evolution of the token F-score of the different models. We can see that

\textsuperscript{2}http://web.science.mq.edu.au/~mjohnson/
\textsuperscript{3}https://github.com/SnippyHolloW/contextual_word_segmentation
\textsuperscript{4}https://github.com/SnippyHolloW/contextual_word_segmentation/tree/master/ProvidenceFinal/Final
context-based models need more data to get good performances (several vocabularies to learn), but they seem more resilient to over-segmentation.

Preliminary results confirm the trend of baseline scores getting slowly worse at 25 and 26 months while with common and split vocab stabilize (not plotted here). We also tried models for which we can have the “common vocabulary” derived only at the level of the collocations (making topic-specific collocations topic-pure as in split vocab for instance), or only at the level of the words (allowing for topic-specific collocations deriving in only common words if needed). Both models are worse than split vocab and with common.

Using a shared global vocabulary while being able to learn (through adaptation) different topic-specific vocabularies does not seem to be a solution: share vocab performs worse than the baseline. Token recall and boundary recall are worse off (see Table 2), suggesting that fewer words are correctly adapted. Maybe that is because this is the only model with two levels of adapted word hierarchies (Word\_\_K and Word). Sharing a lower-level vocabulary (Word) still does not allow for context vocabularies (Word\_\_K) to mix, thus is simply harder to train. Having only one vocabulary per context (split vocab) is a slight improvement over the baseline, even though it is not significant (95% confidence interval) before 22 months. Models allowing for both topic-specific vocabularies and a common vocabulary to be learned are the best: with common is significantly (95% confidence interval) better than the baseline, starting from 20 months (Figure 1). The improvement seems to be due to better token (and boundary) recall (Table 2), suggesting that more words are learned. By looking at their lexicons at 24 months, topic-dependent models have slightly larger lexicon recalls and worse lexicon precisions than the baseline. This means that the additional true word-types that they learn are more frequently correctly used than the false word-types (otherwise the token F-scores would be reversed, e.g. between split vocab and baseline).
Figure 2: Mean token F-scores (and standard deviations) on 20% held-out test data for 6 different random splits of Naima from 11 to 22 months, 500 iterations each. Grey for baseline on test, green and blue for context-dependent models on test and no prefix conditions respectively.

Table 3: Most probable words (∝ P(word|topic = k)) in the 7 recovered topics at test time without topic annotations (no prefix condition) for the with common model (we omitted phonemes clusters yielding non-words).

<table>
<thead>
<tr>
<th>bread</th>
<th>delicious</th>
<th>avocado</th>
<th>pomridge</th>
<th>raisin</th>
<th>biscuit</th>
<th>food</th>
<th>animal</th>
<th>play</th>
<th>clothes</th>
<th>(messy)</th>
<th>verbs</th>
<th>~shapes</th>
</tr>
</thead>
<tbody>
<tr>
<td>elephant</td>
<td>lego</td>
<td>Michael</td>
<td>skinny</td>
<td>stick</td>
<td>bubble</td>
<td>pasta</td>
<td>spiral</td>
<td>squirrels</td>
<td>thumb</td>
<td>pentagon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>owl</td>
<td>doctor</td>
<td>towel</td>
<td>massage</td>
<td>remember</td>
<td>hearing</td>
<td>brush</td>
<td>change</td>
<td>squeeze</td>
<td>pirates</td>
<td>tangled</td>
<td>hammer</td>
<td>oink</td>
</tr>
</tbody>
</table>
7 Conclusion

We have shown that contextual information helps segmenting speech into word-like units. We used topic modeling as a proxy for richer contextual annotations, as (Roy et al., 2012) have shown high correlation between contexts and automatically derived topics. We modified existing Adaptor Grammar segmentation models (Johnson, 2008; Johnson and Goldwater, 2009), to be able to learn topic-specific vocabularies. We applied this approach to a large child directed speech corpus that was previously used for segmentation (Börschinger et al., 2012). Our model with the capacity to use both a topic-specific vocabulary and a common vocabulary (with common) produces better segmentation scores, ending up with at least 2.5% better absolute F-scores than its context-oblivious counterpart (baseline). More generally, both models that learn specialized vocabularies do not get worse F-scores with increasing data (Figure 1). Particularly, they seem to fix a well-known problem of previous models like “colloc-syll” (our baseline), that “overlearn” by over-segmenting frequent morphemes as single words (Börschinger et al., 2012). We have controlled for the additional information of giving the topic (JK), and we have found out that contextual information helps at training time.

It would be interesting to look into the link between semantics and syntax in recovered topics. Further work should integrate syntax (e.g. function words), stress cues and prosody from the audio signal (Börschinger and Johnson, 2014), use even less supervision for contexts, and be applied to other languages. We believe that language acquisition is not a simple sequential process and that segmentation, syntax, and word meaning bootstrap each others. This is only a first step towards integrating multiple sources of information and different modalities at all steps of language acquisition.

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