Learning grammatical categories using paradigmatic representation: Substitute words for language acquisition

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Abstract

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1. Introduction

1.1. Psycholinguistic evidence relevant to substitutes

1.2. Comparison with previous distributional approaches

2. Substitute Words

In this study, we predict the syntactic category of a word in a given context based on its most likely substitute words. Note that the substitute word distribution is a function of the context only and is indifferent to the target word.

St Clair et al. (2010) demonstrated that learning left and right bigrams together was much more effective than learning them individually. Thus it is best to use both the left and the right context when estimating the probabilities for potential lexical substitutes. For example, in *"He lived in San Francisco suburbs."*, the token *San* would be difficult to guess from the left context but it is almost certain looking at the right context. We define

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c_w as the $2n-1$ word window centered around the target word position: $w_{-n+1} \dots w_0 \dots w_{n-1}$. The probability of a substitute word w in a given context c_w can be estimated as:

$$\begin{aligned} P(w_0 = w|c_w) &\propto P(w_{-n+1} \dots w_0 \dots w_{n-1}) && (1) \\ &= P(w_{-n+1})P(w_{-n+2}|w_{-n+1}) \dots P(w_{n-1}|w_{-n+1}^{n-2}) && (2) \\ &\approx P(w_0|w_{-n+1}^{-1})P(w_1|w_{-n+2}^{0}) \dots P(w_{n-1}|w_0^{n-2}) && (3) \end{aligned}$$

where w_i^j represents the sequence of words $w_i w_{i+1} \dots w_j$. In Equation 1, $P(w|c_w)$ is proportional to $P(w_{-n+1} \dots w_0 \dots w_{n+1})$ because the words of the context are fixed. Terms without w_0 are identical for each substitute in Equation 2 therefore they have been dropped in Equation 3. Finally, because of the Markov property of n-gram language model, only the closest $n-1$ words are used in the experiments.

Near the sentence boundaries the appropriate terms were truncated in Equation 3. Specifically, at the beginning of the sentence shorter n-gram contexts were used and at the end of the sentence terms beyond the end-of-sentence utterance were dropped.

To compute substitute probabilities we trained a language model using approximately 6.8 million tokens of child-directed speech data from the CHILDES corpus (MacWhinney, 2000) (excluding sections of [test-set]) We used SRILM (Stolcke, 2002) to build a 4-gram language model with Kneser-Ney discounting. Words that were observed less than 2 times in the LM training data were replaced by UNK tags, which gave us a vocabulary size of 21734. [What is the test data? Where should we put this?] [perplexity]

1. We need to clarify the tag set that is used during the experiments. May be it is better to give the whole mapping as an Appendix section.
2. Data statistics (it is common to all experiments)

3. Experiment 1: corpus analysis

In this section we replicate the corpus analyses of St Clair et al. (2010) and Mintz (2003).

3.1. Input Corpora

In order to be consistent with St Clair et al. (2010) and Mintz (2003), we use the same six corpora of child-directed speech from the CHILDES corpus

(MacWhinney, 2000): Anne and Aran (Theakston, Lieven, Pine & Rowland, 2001), Eve (Crystal, 1974), Naomi (Sachs, 1983), Nina (Suppes, 1974), Peter (Bloom, Hood & Lightbown, 1974; Bloom, Lightbown, Hood, Bowerman, Maratsos & Maratsos, 1975). Following Mintz (2003) we only analyze the adult utterances in sessions where the target child is 2.6 years old or younger.

3.1.1. Preprocessing

The grammatical category of words in CHILDES are extracted by first applying the MOR parser (MacWhinney, 2000) and then using the POST disambiguator (Sagae, MacWhinney & Lavie, 2004). The accuracy of CHILDES grammatical categories is approximately 95% (Parisse et al., 2000) and it is encoded in the MOR line of the CHILDES corpus.

We apply the following pre-processing steps (St Clair, Monaghan & Christiansen, 2010) initial to our analyses:

- All punctuation, pause, trailing off and interruption marks are treated as utterance boundary marks.
- Repetitions of a word are kept in the text and their grammatical categories are automatically set to the grammatical category of the original word.
- Words that are grammatically necessary but not spoken are deleted (grammatical omissions).
- **Short usages ??**
- **Frames do not include utterance boundaries. Mintz (2003)**

3.2. Method

Word sequences that consist of three words and do not contain any utterance boundaries are extracted for each child corpus seperately. The first and third words of the word sequences are treated as frame elements while the middle word is the target word that we want to categorize. The correct grammatical category of target words are extracted from CHILDES.

3.3. Results

4. Experiment 2: computational modeling of substitutes

St Clair et al. (2010) used a feed-forward connectionist model to compare the effect of distributional cues from various frame types on the grammatical category problem. We adopt their framework to compare the paradigmatic representation (substitute words) with the syntagmatic representation (flexible frames).

A prototypical connectionist model consists of input, hidden and output layers. Input and output layers are connected to each other through the hidden layer. The behavior of the output units are determined by the activity of the hidden layers which is triggered by the input layer.

4.1. Method

We train two connectionist models to compare flexible frames ($aX + Xb$) to the substitute words ($a * b$).

4.2. Architecture

For each model we input the distributional information to the feed-forward connectionist model in the following way,

- $aX+Xb$ **model:** The first and second half of the input units correspond to the preceding bigram (a) and the succeeding bigram (b), respectively. Thus two input units are activated for each target word.

- $a*b$ **model:** Each input unit represents a distinct substitute and input units that correspond to the substitutes of the target word are set to the number of their occurrences in the sampled subsitute set.

Table 1 presents the number of input layer units of syntagmatic and paradigmatic representation based models on each child corpus seperately. The number of distinct frames is fixed for any given corpus while the number of distinct substitutes varies due to the random sampling of substitutes.

Each output unit represents a distinct grammatical category therefore the models are expected to produce only one active (non-zero) output unit for each target word. If there are more than one active units present in the

Table 1: Number of input layer units of the flexible frame ($aX + Xb$) and the substitute based models are summarized. Substitute based model samples 16 substitutes per target word. Standard errors are reported in parentheses.

Child	Distinct $aX + Xb$	Distinct *Substitutes*
Anne	3601	4999.4 (39.86)
Aran	4857	6066.3 (40.84)
Eve	2928	4261.1 (32.18)
Naomi	2396	3366.3 (39.11)
Nina	3084	4936.3 (36.29)
Peter	2835	4290.5 (34.56)

output layer[1], the target word is assigned to the corresponding grammatical category of the largest unit.

Both models have 10 output units due to the standard labeling (Mintz, 2003).

Number of hidden units is set to 200 and initialized randomly for each model. **backprobagation(0.1), learning rate, sigmoid...**

4.3. Training and Testing

We analyze each child corpus seperately and apply 10-fold cross validation to measure model performances. 10-fold cross validation randomly splits the sentences of each corpora into 10 sentence wise equal sized subsamples. Thus target words from the same sentence are observed in the same subsample. A single subsample is kept as the test data while remaining 9 samples are used as the training data. The process is repeated until all subsamples are used exactly once as the test data and report the average accuracy of the 10 runs. The main advantage of the cross validation is that each subsample is observed both as test and training data.

To compare the effects of paradigmatic representation with the syntagmatic one we test both models on each child corpus using the same 10-fold cross validation split.

[1] why neural network produces more than one active unit.

Table 2: 10 fold cross-validation accuracy of flexible frame ($aX + Xb$) and substitute based models on each child corpus are summarized. The training phase on each corpus is stopped after 50K word patterns are presented and the standard labeling is used. Substitute based model samples 16 substitutes per target word. Standard errors are reported in parentheses.

Child	$aX + Xb$	*Substitutes*
Anne	.7545 (.0147)	**.8273 (.0087)**
Aran	.7164 (.0151)	**.8136 (.0096)**
Eve	.7605 (.0104)	**.8378 (.0199)**
Naomi	.7438 (.0156)	**.8165 (.0147)**
Nina	.7745 (.0199)	**.8494 (.0073)**
Peter	.7630 (.005)	**.8437 (.0061)**

5. Experiment 2

Number of subsitutes. We need to show 16 is better than 1 but 16+ is same

5.1. Input Corpora

5.2. Method

5.3. Results

6. Experiment 3

N-gram order 2,3

7. Experiment 4

What happens when we change the data size?
What happens when we change the vocabulary threshold?

7.1. Input Corpora

7.2. Method

7.3. Results

8. Experiment 5

Left/rigth context substitute

8.1. Input Corpora

8.2. Method

8.3. Results

9. Experiment 6

Other languages that we have in CHILDES

10. Experiment 7

What happens if some of the words are given (semi-supervised setting)

10.1. Input Corpora

10.2. Method

10.3. Results

11. General Discussion

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