# Learning languages from positive examples with dependencies

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## Abstract

We investigate learning dependency grammar from positive data, in Gold's identification in the limit model. Examples are dependency trees. For this, we introduce reversible lexical dependency grammars which generate a significant class of languages. We have demonstrated that reversible dependency languages are learnable. We provide a  $O(n^2)$ -time, in the example size, algorithm. Our objective is to contribute to design and the understanding of formal process of language acquisition. For this, dependency trees play an important role because they naturally appear in every tree phrase structure.

#### 1. An identification paradigm

From Tesniére (Tesnière, 1959) seminal study, and from ideas of Mel'čuk (Mel'čuk, 1988), we propose a two tier communication process between two speakers, see Figure 1. Jean transmits a sentence to Marie. At the first stage, Jean generates a structural sentence, like the following dependency tree



Then, Jean transforms it into a linear phrase, *the rabbit runs fast*, and send it to Marie. Now, Marie has to inverse the two tier process of Jean. For this, she has (i) to recover the structural sentence from the linear sentence ( $\eta^{-1}$ ), (ii) to build/update/improve her grammar in order to understand the message, and to generate other messages ( $\theta^{-1}$ ). In the setting of natural language learning, parsers perform the first task of Marie. Roughly speaking, parsing corresponds to inverse  $\eta$ , that is to compute  $\eta^{-1}$ .

We are investigating identification, that is exact learning, of dependency tree languages. The leading idea is that data used to learn are dependency trees. Dependencies are semantic annotation by additional informations which facilitates the learning process. Such data are widely available and come from a lot of computational linguistic formal grammars such as LFG, TAG, categorial grammar and interaction grammar. The relations between those formalism are explained in the special issue of TAL (Kahane, 2000) on dependency grammars.

The data available are positive examples of a language, that is a sequence of dependency trees. Our hypothesis is that the computation of  $\theta$  is reversible, that is the inputs can always be deduced from the outputs. So, identification corresponds to inverse  $\theta$ . For this, we give a sufficient condition of reversibility on the grammars ( $G_0$ ). We show that the class of reversible dependency tree languages is efficiently identifiable in Gold's model (Gold, 1967). That is, given a finite sequence of examples of a reversible language, we determine a reversible grammar that generates it. We refer to (Jain *et al.*, 1999) for further explanations. Our study leans on the work of Angluin (Angluin, 1982) on learning languages produced by deterministic and reversibles finite automaton. It is also closely related to Sakakibara (Sakakibara, 1992) work on reversible context free grammars and to Kanazawa (Kanazawa, 1998) work on rigid categorial grammars.



Figure 1: A two tier communication process

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### 2. Lexical dependency grammar

Following Dikovsky and Modina (Dikovsky and Modina, 2000), we present a class of projective dependency grammars which was introduced by Hays (Hays, 1961) and Gaifman (Gaifman, 1965).

A *lexical dependency grammar* (LDG)  $\Gamma$  is a quadruplet  $\langle \Sigma, N, P, S \rangle$ , where  $\Sigma$  is the set of terminal symbols, N is the set of non-terminal symbols,  $S \in N$  is the start symbol, and P is the set of productions. Each production

is of the form  $X \to U_1 \dots U_p \ a \ V_1 \dots V_q$ , where  $X \in N$ , each  $U_i$  and  $V_j$  are in  $\Sigma \cup N$ . The terminal symbol a is called the *head* of the production. In other words, the head is the root of the flat tree formed by the production right handside. Actually, if we forget dependencies, we just deal with context free grammars.

**Example 1.** The grammar  $\Gamma_0 = \langle \{a, b\}, \{S\}, P, S \rangle$  where P consists

$$S \rightarrow a \begin{array}{c} & & & & \\ S \rightarrow a \begin{array}{c} S \end{array} \begin{array}{c} & & & \\ b \end{array} \begin{array}{c} & & \\ a \end{array} \begin{array}{c} \\ b \end{array}$$

Partial dependency trees are recursively defined as follows.

1. S is a partial dependency tree generated by  $\Gamma$ .

2. If  $\dots X \dots b \dots$  is a partial dependency tree generated by  $\Gamma$ , and if

 $X \to U_1 \dots U_p \ a \ V_1 \dots V_q$  is a production of  $\Gamma$ , then



is a partial dependency tree generated by  $\Gamma$ .

A *dependency tree* generated by a LDG  $\Gamma$  is a partial dependency tree of  $\Gamma$  in which all nodes are terminal symbols. The language  $\mathcal{D}(\Gamma)$  is the set of all dependency trees generated by  $\Gamma$ .

**Example 2.** The language generated by  $\Gamma_0$  of Example 1 is

$$\mathcal{D}(\Gamma_0) = \{ a \ b, a \ a \ b \ b, a \ a \ a \ b \ b, \dots \}$$

Without dependencies, we recognize the context free language  $\{a^n b^n / n > 0\}$ .

#### 3. Reversible LDG

A LDG grammar  $\Gamma$  is *reversible* if the conditions **R1**, **R2** and **R3** of Figure 2 are satisfied. The class of *reversible dependency tree languages* is the class of languages generated by reversible LDG.

## 4. The learning algorithm

The learning algorithm works as follows. The input is a finite set H of positive examples which are dependency trees. Define TG(H) as the grammar constructed from all productions outputed by TG(w, S), for each  $w \in H$ . The function TG is described in Figure 3.

# Stage 0 $G_0 = \operatorname{TG}(H)$ .

**Stage n+1** The grammar  $G_{n+1}$  is defined by applying one of the rule of Figure 2.

**R1** If 
$$X \to \mathbf{U} \stackrel{\frown}{a} \mathbf{V}$$
 and if  $Y \to \mathbf{U} \stackrel{\frown}{a} \mathbf{V}$ , then  $X = Y$ .  
**R2** If  $X \to \stackrel{\frown}{\alpha} \stackrel{\frown}{Y \stackrel{\frown}{\beta}} \stackrel{\frown}{a} \stackrel{\frown}{\gamma}$  and if  $X \to \stackrel{\frown}{\alpha} \stackrel{\frown}{Z \stackrel{\frown}{\beta}} \stackrel{\frown}{a} \stackrel{\frown}{\gamma}$ , then  $Y = Z$ , where  $Y, Z \in N$ .  
**R3** If  $X \to \stackrel{\frown}{\alpha} \stackrel{\frown}{a} \stackrel{\frown}{\beta} \stackrel{\frown}{Y \stackrel{\frown}{\gamma}}$  and if  $X \to \stackrel{\frown}{\alpha} \stackrel{\frown}{a} \stackrel{\frown}{\beta} \stackrel{\frown}{Z \stackrel{\frown}{\gamma}}$ , then  $Y = Z$ , where  $Y, Z \in N$ .  
We write  $\stackrel{\frown}{\alpha} \stackrel{\frown}{a} \stackrel{\frown}{\beta}$  for  $\stackrel{\frown}{\alpha_1} \dots \stackrel{\frown}{\alpha_p} \stackrel{\frown}{a} \stackrel{\frown}{\beta_1} \dots \stackrel{\frown}{\beta_q}$ .

Figure 2: Reversibility conditions and reduction rules.

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Function \operatorname{TG}(w, X)

Inputs : w is a dependency tree,

X is a non-terminal symbol.

if w \in \Sigma

then Output X \to w

if w = u_1 \dots u_p a v_1 \dots v_q

then Take new U_1, \dots, U_p and V_1, \dots, V_q

Output X \to U_1 \dots U_p a V_1 \dots V_q

for i = 1 to p do \operatorname{TG}(u_i, U_i)

for i = 1 to q do \operatorname{TG}(v_i, V_i)
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Figure 3: TG(w, X) recognizes exactly w, i.e.  $\mathcal{D}(TG(w, X)) = \{w\}$ 

The process terminates at some stage m because the number of grammar productions decreases at each stage. So, put  $\phi(H) = G_m$ .

**Theorem 3.**  $\phi$  learns the class of reversible dependency tree languages.

The learning algorithm is incremental and runs in quadratic time in the size of the examples. Our algorithm is implemented as a Java prototype which is accessible from http://www.loria.fr/~ besombes.

**Example 4.** 
$$H = \{$$
 the rabbit is very fast, the rabbit is fast, the rabbit is very fast}, the rabbit is fast, the rabbit is very fast},

The productions of  $G_0 = TG(H)$  are

$$TG(the rabbit is very fast, S) = \begin{cases} \overrightarrow{S} \rightarrow X_1 \text{ is } X_2, \\ X_1 \rightarrow X_3 \text{ rabbit}, \\ X_2 \rightarrow X_4 \text{ fast}, \\ X_3 \rightarrow the, \\ X_4 \rightarrow very \end{cases}$$
$$TG(the rabbit is fast, S) = \begin{cases} \overrightarrow{S} \rightarrow X_5 \text{ is } X_6, \\ \overrightarrow{X_5} \rightarrow X_7 \text{ rabbit}, \\ X_6 \rightarrow fast, \\ X_7 \rightarrow the. \end{cases}$$
$$TG(the rabbit is very very fast\}, S) = \begin{cases} \overrightarrow{S} \rightarrow X_8 \text{ is } X_9, \\ X_8 \rightarrow X_{10} \text{ rabbit}, \\ X_{10} \rightarrow the, \\ X_{10} \rightarrow the, \\ X_{12} \rightarrow very \end{cases}$$

Second, we apply **R1** to identify  $X_4 = X_{12}$ ,  $X_3 = X_7 = X_{10}$ .

$$S \rightarrow X_{1} \text{ is } X_{2} \qquad X_{3} \rightarrow the \qquad X_{5} \rightarrow X_{3} \text{ rabbit} \qquad X_{8} \rightarrow X_{3} \text{ rabbit} \qquad X_{1} \rightarrow X_{3} \text{ rabbit} \qquad X_{4} \rightarrow very \qquad X_{6} \rightarrow fast \qquad X_{9} \rightarrow X_{11} \text{ fast} \qquad X_{2} \rightarrow X_{4} \text{ fast} \qquad S \rightarrow X_{5} \text{ is } X_{6} \qquad S \rightarrow X_{8} \text{ is } X_{9} \qquad X_{11} \rightarrow very X_{4}$$

We apply **R1** to identify  $X_1 = X_8$  and  $X_5 = X_1$ .

$$S \rightarrow X_{1} \text{ is } X_{2} \qquad X_{4} \rightarrow very \qquad S \rightarrow X_{1} \text{ is } X_{9}$$

$$X_{1} \rightarrow X_{3} \text{ rabbit} \qquad S \rightarrow X_{1} \text{ is } X_{6} \qquad \bigvee \qquad X_{1} \text{ is } X_{6} \qquad X_{1} \text{ is } X_{6} \qquad X_{1} \text{ is } X_{1} \text{ is }$$

Now, we merge  $X_2 = X_6 = X_9$  by applying **R3** on S rules.

$$S \rightarrow X_{1} \text{ is } X_{2} \qquad X_{2} \rightarrow X_{11} \text{ fast} \quad X_{4} \rightarrow \text{very}$$

$$X_{1} \rightarrow X_{3} \text{ rabbit} \quad X_{2} \rightarrow \text{fast} \qquad X_{11} \rightarrow \text{very} X_{4}$$

$$X_{2} \rightarrow X_{4} \text{ fast} \qquad X_{3} \rightarrow \text{the}$$

Lastly, we apply **R2** on  $X_2$  rules by merging  $X_4 = X_{11}$ . We obtain the final grammar:

$$S \rightarrow X_{1} \text{ is } X_{2} \qquad X_{2} \rightarrow fast \qquad X_{4} \rightarrow very$$

$$X_{1} \rightarrow X_{3} \text{ rabbit} \qquad X_{3} \rightarrow the \qquad X_{4} \rightarrow very X_{4}$$

$$X_{2} \rightarrow X_{4} \text{ fast}$$

## 5. Related works

• Sakakibara (Sakakibara, 1992) gives a learning algorithm to infer reversible context free languages from skeleton parse trees. The definition of reversible grammar is very similar to ours. However, we distinguish between both

productions  $X \to Y \stackrel{\frown}{a \ b \ Z}$  and  $X \to Y \stackrel{\frown}{a \ b \ Z}$ , unlike (Sakakibara, 1992) in which they are considered identical.

 Kanazawa (Kanazawa, 1998) studies inference of several classes of categorial grammars from functor structures, based on counting the number of categories associated to a terminal symbol. It is not difficult to faithfully translate rigid grammar in reversible dependency grammars.

The defect of learning from structures is that examples usually depend on the implicit grammar that we have to guess. It appears that it is not the case in our approach because we deal with tree languages, and so is seemingly more natural.

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