# Dependency parsing & Dependency parsers

Lecture 11

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## Syntactic formalisms for natural language parsing

IA161, FI MU autumn 2011

## **Study materials**

Course materials and homeworks are available on the following web site:

https://is.muni.cz/course/fi/autumn2011/IA161

Refer to Dependency Parsing, Synthesis: Lectures on Human Language Technologies, S. kübler, R. McDonald and J. Nivre, 2009

## Outline

- Introduction to Dependency parsing methods
- Dependency Parsers

## **1. Introduction to Dependency** parsing

## Motivation

**a.** dependency-based syntactic representation seem to be useful in many applications of language technology: machine translation, information extraction

- $\rightarrow$  transparent encoding of predicate-argument structure
- **b.** dependency grammar is better suited than phrase structure grammar for language with free or flexible word order
- $\rightarrow$  analysis of diverse languages within a common framework

## Motivation (Cont.)

**c.** leading to the development of accurate syntactic parsers for a number of languages

 $\rightarrow$  combination with machine learning from syntactically annotated corpora (e.g. treebank)

## Dependency parsing

"Task of automatically analyzing the dependency structure of a given input sentence"

## Dependency parser

"Task of producing a labeled dependency structure of the kind depicted in the follow figure, where the words of the sentence are connected by typed dependency relations"



## Definitions of dependency graphs and dependency parsing

 Dependency graphs: syntactic structures over sentences

**Def. 1.**: A *sentence* is a sequence of tokens denoted by

$$S = W_0 W_1 \dots W_n$$

**Def. 2.**: Let  $R = \{r_1, \dots, r_m\}$  be a finite set of *possible* dependency relation types that can hold between any two words in a sentence. A relation type  $r \in R$  is additionally called an *arc label*.

## **Definitions of dependency graphs and dependency parsing (Cont.)**

 Dependency graphs: syntactic structures over sentences

**Def. 3.**: A dependency graph G=(V, A) is a labeled directed graph, consists of nodes, V, and arcs, A, such that for sentence  $S = w_0 w_1 \dots w_n$  and label set R the following holds:

- 1.  $V \subseteq \{W_0 W_1 \dots W_n\}$
- 2.  $A \subseteq V \times R \times V$
- 3. if  $(w_{i}, r, w_{j}) \in A$  then  $(w_{i}, r', w_{j}) \notin A$  for all  $r' \neq r$

## Approach to dependency parsing

#### a. data-driven

it makes essential use of machine learning from linguistic data in order to parse new sentences

#### b. grammar-based

it relies on a formal grammar, defining a formal language, so that it makes sense to ask whether a given input is in the language defined by the grammar or not.

→ Data-driven have attracted the most attention in recent years.

## Data-driven approach

according to the type of parsing model adopted,

the *algorithms used to learn the model from data* the *algorithms used to parse new sentences with the model* 

#### a. transition-based

start by defining a transition system, or state machine, for mapping a sentence to its dependency graph.

#### **b.** graph-based

start by defining a space of candidate dependency graphs for a sentence

## Data-driven approach (Cont.)

#### a. transition-based

learning problem: induce a model for predicting the next state transition, given the transition history

parsing problem: construct the optimal transition sequence for the input sentence,, given induced model

#### **b.** graph-based

learning problem: induce a model for assigning scores to the candidate dependency graphs for a sentence

parsing problem: find the highest-scoring dependency graph for the input sentence, given induced model

## **Transition-based Parsing**

- Transition system consists of a set C of parser configurations and of a set D of transitions between configurations.
- Main idea: a sequence of valid transitions, starting in the *initial configuration* for a given sentence and ending in one of several *terminal configurations*, defines a valid dependency tree for the input sentence.

$$D_{1'm} = d_1(c_1), \dots, d_m(c_m)$$

#### Definition

Score of  $D_{1'm}$  factors by configuration-transition pairs  $(c_i, d_j)$ :  $s(D_{1'm}) = \sum_{i=1}^{m} s(c_i, d_j)$ 

#### Learning

**Scoring function**  $s(C_i, d_i)$  for  $d_i(C_i) \in D_{1'm}$ 

#### Inference

Search for highest scoring sequence  $D^*_{1,m}$  given  $s(c_i, d_i)$ 

## **Transition-based Parsing (Cont.)**

## Inference for transition-based parsing

#### Common inference strategies:

- Deterministic [Yamada and Matsumoto 2003, Nivre et al. 2004]
- Beam search [Johansson and Nugues 2006, Titov and Henderson 2007]
- Complexity given by upper bound on transition sequence length

## Transition system

- Projective O(n) [Yamada and Matsumoto 2003, Nivre 2003]
- Limited non-projective O(n) [Attardi 2006, Nivre 2007]
- Unrestricted non-projective O(n2) [Nivre 2008, Nivre 2009]

## **Transition-based Parsing (Cont.)**

## Learning for transition-based parsing

## • Typical scoring function:

>  $s(c_i, d_i) = \mathbf{w} \cdot \mathbf{f}(c_i, d_i)$  where  $\mathbf{f}(c_i, d_i)$  is a feature vector over configuration  $c_i$  and transition  $d_i$  and  $\mathbf{w}$  is a weight vector  $[w_i = weight of feature f_i(c_i, d_i)]$ 

## Transition system

- Projective O(n) [Yamada and Matsumoto 2003, Nivre 2003]
- Limited non-projective O(n) [Attardi 2006, Nivre 2007]
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#### Problem

Learning is local but features are based on the global
 <sup>15</sup>
 history

## **Graph-based Parsing**

• For a input sentence S we define a graph  $G_s = (V_s, A_s)$  where

$$V_{s} = \{w_{0}, w_{1}, \dots, w_{n}\}$$
 and

 $A_{s} = \{(w_{i'}, w_{j'}, l) \mid w_{i'}, w_{j} \in V \text{ and } l \in L\}$ 

- Score of a dependency tree *T* factors by subgraphs  $G_{s_i}$  ....., *Gs*:  $s(T) = \sum_{i=1}^{m} s(G_i)$
- Learning: Scoring function  $S(G_i)$  for a subgraph  $G_i \in T$
- Inference: Search for maximum spanning tree scoring sequence T\* of G<sub>s</sub> given S(G<sub>i</sub>)

## **Graph-based Parsing (Cont.)**

## Learning graph-based models

#### • Typical scoring function:

- s(G<sub>i</sub>)=w f(G<sub>i</sub>) where f(G<sub>i</sub>) is a high-dimensional feature vector over subgraphs and w is a weight vector [w<sub>j</sub> = weight of feature f<sub>j</sub> (G<sub>i</sub>)]
- Structured learning [McDonald *et al.* 2005a, Smith and Johnson 2007]:
  - Learn weights that maximize the score of the correct dependency tree for every sentence in the training set

#### Problem

Learning is global (trees) but features are local (subgraphs)

Grammar-based approach

#### a. context-free dependency parsing

exploits a mapping from dependency structures to CFG structure representations and reuses parsing algorithms originally developed for CFG  $\rightarrow$  chart parsing algorithms

#### b. constraint-based dependency parsing

- > parsing viewed as a constraint satisfaction problem
- grammar defined as a set of constraints on well-formed dependency graphs
- finding a dependency graph for a sentence that satisfies all the constraints of the grammar (having the best score)

## Grammar-based approach (Cont.)

#### a. context-free dependency parsing

Advantage: Well-studied parsing algorithms such as CKY, Earley's algorithm can be used for dependency parsing as well.

 $\rightarrow$  need to convert dependency grammars into efficiently parsable context-free grammars; (e.g. *bilexical CFG*, Eisner and Smith, 2005)

#### **b.** constraint-based dependency parsing

defines the problem as constraint satisfaction

- Weighted constraint dependency grammar (WCDG, Foth and Menzel, 2005)
- > Transformation-based CDG

## **2. Dependency parsers**

## > Trainable parsers

- Probabilistic dependency parser (Eisner, 1996, 2000)
- MSTParser (McDonald, 2006)-graph-based
- MaltParser (Nivre, 2007, 2008)-transition-based
- K-best Maximum Spanning Tree Dependency Parser (Hall, 2007)
- Vine Parser
- ISBN Dependency Parser
- Parsers for specific languages
  - Minipar (Lin, 1998)
  - WCDG Parser (Foth *et al.*, 2005)
  - Pro3Gres (Schneider, 2004)
  - Link Grammar Parser (Lafferty *et al.*, 1992)
  - CaboCha (Kudo and Matsumoto, 2002)

## MaltParser

#### Data-driven dependency parsing system (Last version, 1.6.1, J. Hall, J. Nilsson and J. Nivre)

- Transition-based parsing system
- Implementation of inductive dependency parsing
- Useful for inducing a parsing model from treebank data
  - Useful for parsing new data using an induced model

<u>Useful links</u> http://maltparser.org

## **Components of system**



## **Running system**

• Input: part-of-speech tags or word forms

1	Den blir	_	PO	PO BV	DP PS	2	SS ROO	т	_	_	
3	gemensam	-	v	AJ	AJ	0	2	SP	—	-	
4	för	_	PR	PŔ	_	2	OA		_	_	_
5	alla	_	PO	PO	TP	6	DT		_	_	
6	inkomsttagare oavsett		PR	N PR	NN	HS 2	4 AA	PA		_	_
8	civilstånd	-		N	ΝN	SS	7	PA	—	-	
9		_	P	IP	_	2	IP		_	_	_

• Output: column containing a dependency label



#### Minimum Spanning Tree Parser (Last version, 0.2, R. McDonald *et al.*, 2005, 2006)

Graph-based parsing system

<u>Useful links</u> http://www.seas.upenn.edu/~strctlrn/MSTParser/MSTParser.html

## **Running system**

#### • Input data format:

w1 w2 wn	
p1 p2 pn	Where, - w1 wn are the n words of the sentence (tab deliminated)
l1 l2 ln	<ul> <li>p1 pn are the POS tags for each word</li> <li>l1 In are the labels of the incoming edge to each word</li> </ul>
d1 d2 d2	- d1 dn are integers representing the postition of each words parent

For example, the sentence "John hit the ball" would be:							
John hit the N V D SBJ ROOT 2 0 4	Ν						

• Output: column containing a dependency label

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## **Comparing parsing accuracy** Graph-based Vs. Transition-based MST Vs. Malt

Language	MST	Malt
Arabic	66.91	66.71
Bulgarian	87.57	87.41
Chinese	85.90	86.92
Czech	80.18	78.42
Danish	84.79	84.77
Dutch	79.19	78.59
German	87.34	85.82
Japanese	90.71	91.65
Portuguese	86.82	87.60
Slovene	73.44	70.30
Spanish	82.25	81.29
Swedish	82.55	84.58
Turkish	63.19	65.68
Average	80.83	80.75

Presented in *Current Trends in Data-Driven Dependency Parsing* by Joakim Nivre, 2009

## Link Parser

#### Syntactic parser of English, based on the Link Grammar

## (version, 4.7.4, Feb. 2011, D. Temperley, D, Sleator, J. Lafferty, 2004)

- Words as blocks with connectors + or -
- Words rules for defining the connection between the connectors
  - Deep syntactic parsing system

#### <u>Useful links</u>

http://www.link.cs.cmu.edu/link/index.html http://www.abisource.com/ • Example of a parsing in the Link Grammar:

let's test our proper sentences!

http://www.link.cs.cmu.edu/link/submit-sentence-4.html

#### John gives a book to Mary.



## Some fans on Friday will be seeking to add another store-opening shirt to collections they've assembled as if they were rare baseball cards.



## **WCDG** parser

#### Weighted Constraint Dependency Grammar Parser

## (version, 0.97-1, May, 2011, W. Menzel, N. Beuck, C. Baumgärtner )

- incremental parsing
- syntactic predictions for incomplete sentences
  - Deep syntactic parsing system

<u>Useful links</u>

http://nats-www.informatik.uni-hamburg.de/view/CDG/ParserDemo