Dependency Parsing

Language Technology 1
WS 2013

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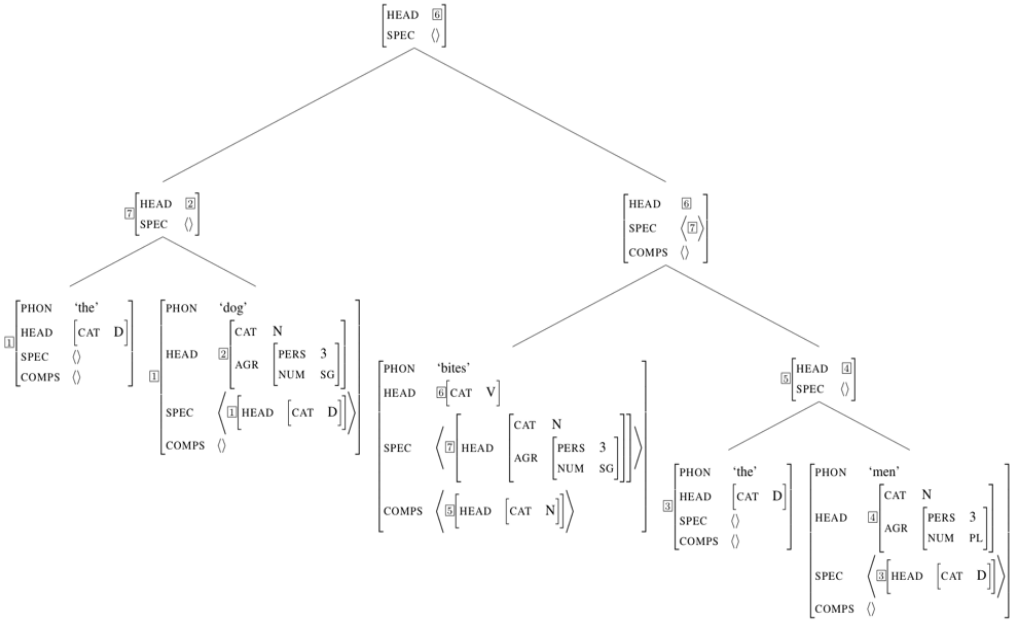
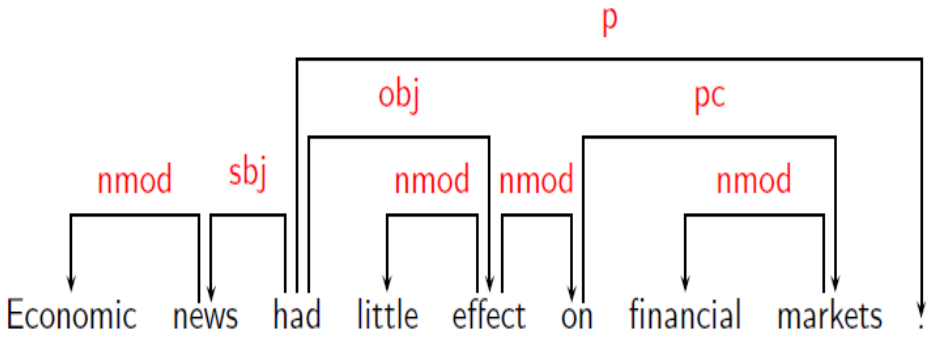
(slides based on Alexander Volokh)

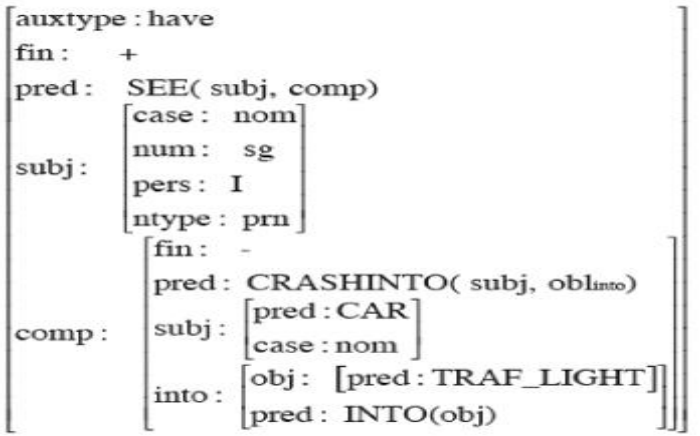
Overview

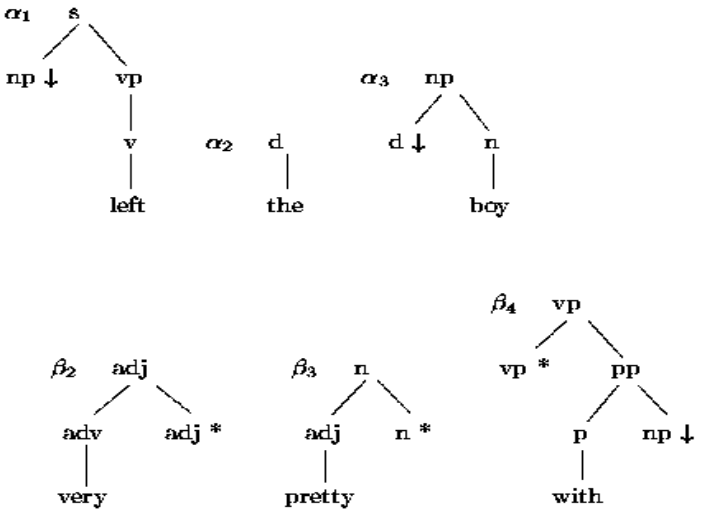
- Dependency Grammar vs Dependency Parsing
- Transition-Based vs Graph-Based Dependency Parsing

Syntactic Theories









Dependency Representation

- The basic idea:

Syntactic structure consists of lexical items, linked by

binary, asymmetric, directed, anti-reflexive, anti-transitive, labeled

relations called dependencies.

- A → B; <B,A>

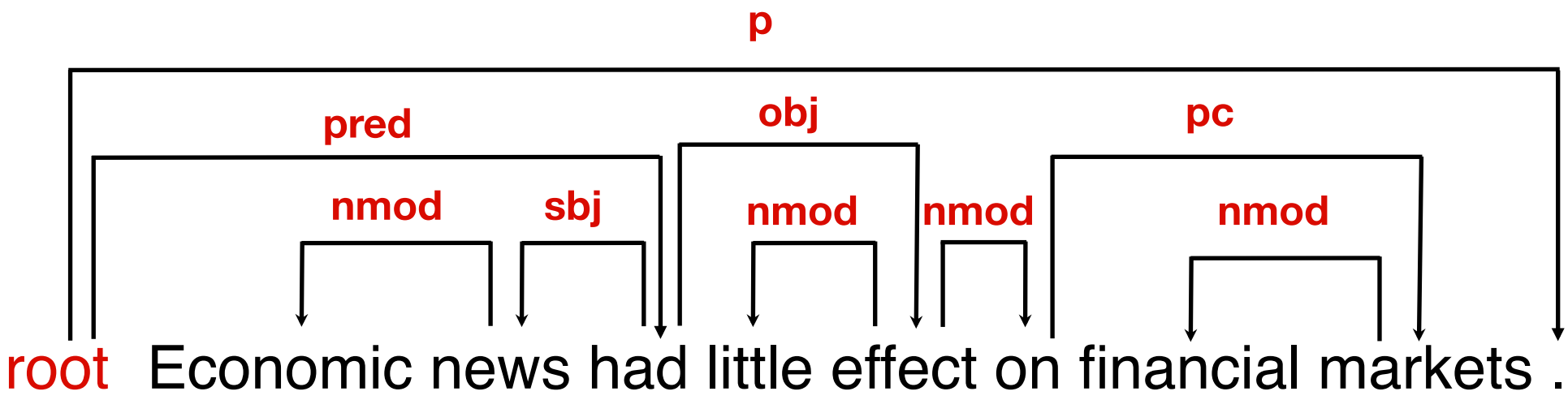
(A is head/parent/governor; B is dependent/child/subordinate)

- Syntactic structures are usually trees, i.e. they have the following properties:

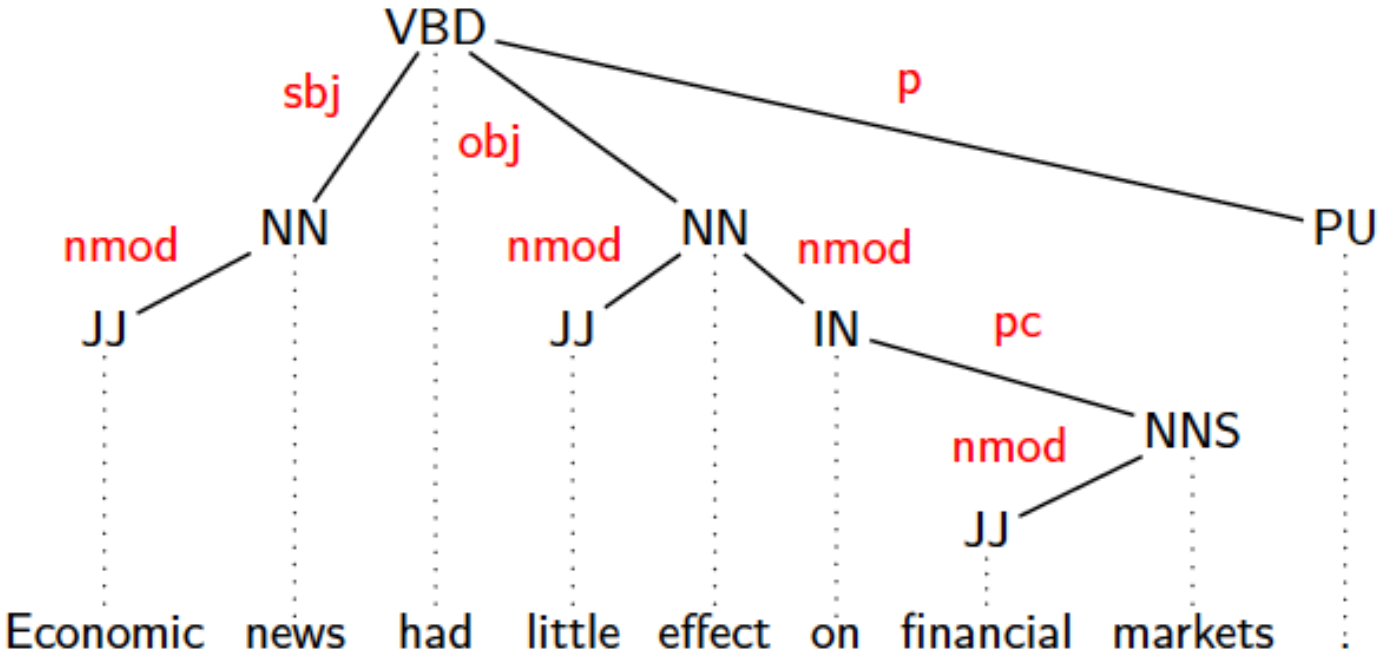
connectedness, single-headiness, rooted, acyclicity, (projectivity)

Connected, A-cyclic, Single-head

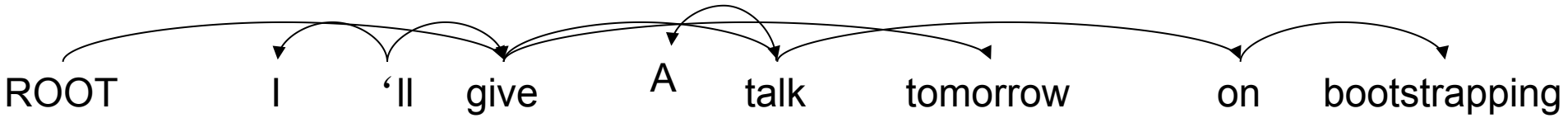
- A syntactic structure is complete (connected)
- A syntactic structure is hierarchical (azyklisch)
- Each word has at most one head (single head)
- Adding a special root-node can Completeness can enforce connectedness.



Example of a Projective Dependency Tree



Nonprojective Syntax



$that_{NOM}$ my_{ACC} may-know $glory_{NOM}$ $going\text{-}gray_{ACC}$

That glory shall last till I go gray

How would we parse this?

Slide from Smith & Smith, EMNLP, 2007

Dependency Grammar

- History:

ancient Greek, Sanskrit, Latin, Arabic, medieval Europe, 1900s

- Problematic phenomena:

coordination, no groupings, auxiliaries

- Variations:

single vs multiple layers (morphology, syntax), different tagsets and structures (Stanford vs CoNLL)

Dependenzparsing

The problem

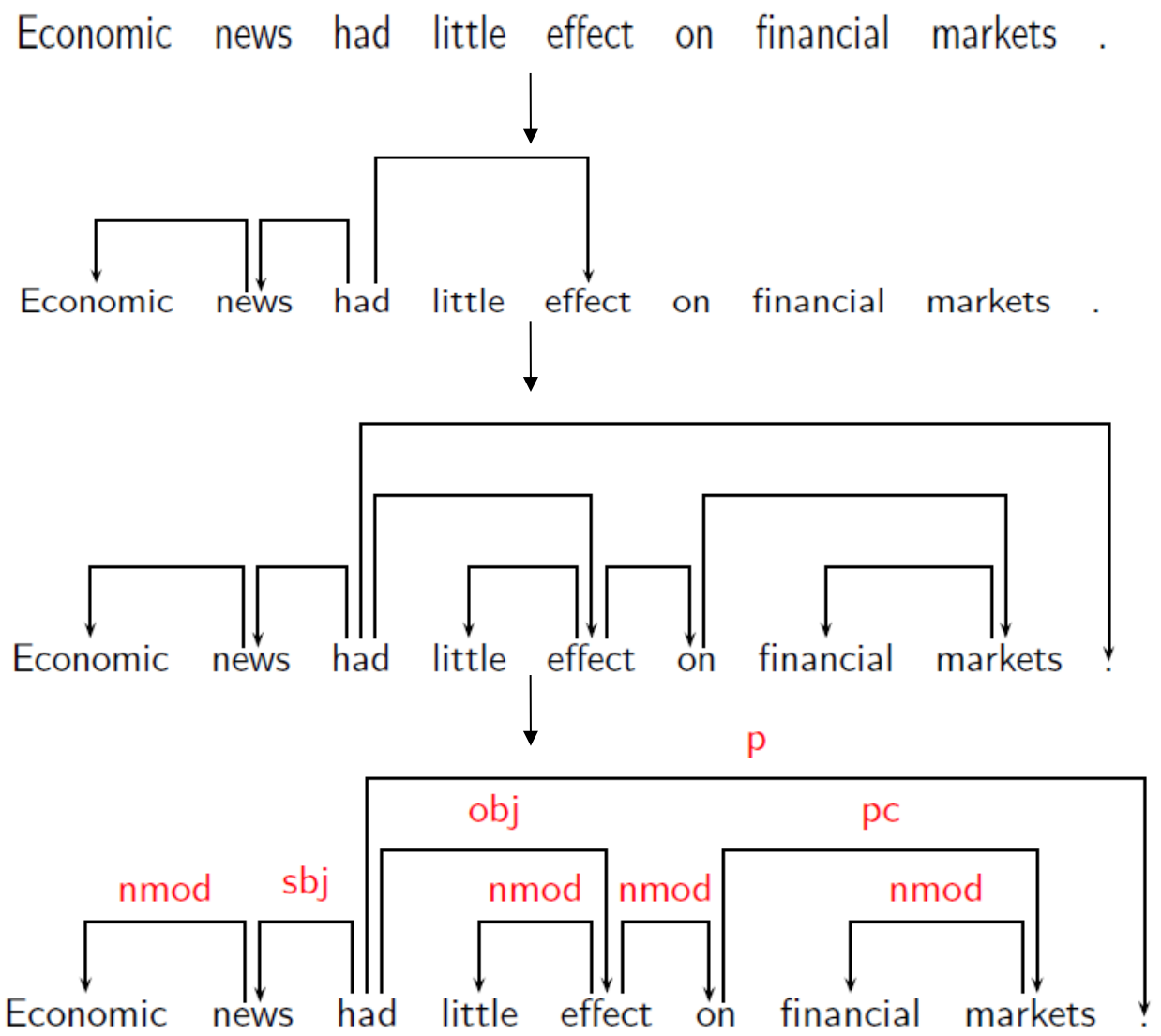
Input: Sentence $x = w_0, w_1, \ldots, w_n$ with $w_0 =$ root

Output: dependency graph $G = (V, A)$ for x whereby:

$V = \{0, 1, \ldots, n\}$ is the node set

A is the edge set, i.e., $(i, j, k) \in A$ represent a dependency from w_i to w_j with label $l_k \in L$

Parsing


Economic news had little effect on financial markets .
Economic news had little effect on financial markets .
Economic news had little effect on financial markets !
p
obj
pc
nmod
sbj
nmod
nmod
nmod
Economic news had little effect on financial markets !

Dependency Parsing

- Easy to implement
  - no artifical nodes
  - linear complexity possible (deterministic parsing)
- Easy to evaluate
  - attachment scores are very straightforward
- Very expressive
  - Suitable for free word order languages
- Useful representations
  - Very close to semantics, which is very often done next

Applications

- Almost any language technology can profit from dependency parsing:
- Machine Translation
- Information Extraction
- Textual Entailment
- Question Answering
- Summarisation
- Text Generation

Grammar vs Data-Driven

- Rule systems:
- Lists of words for every category
- Which categories occur with which categories
- Valency
- Data-driven systems:
- Use treebanks to learn how to link words
- Dependency treebanks are available for many languages (CoNLL-X shared task)

Transition-Based vs Graph-Based

- Two predominant parser types

- similar performance

- completely different approaches

- Transition-based:

- the result is constructed after a series of transitions (local decisions)

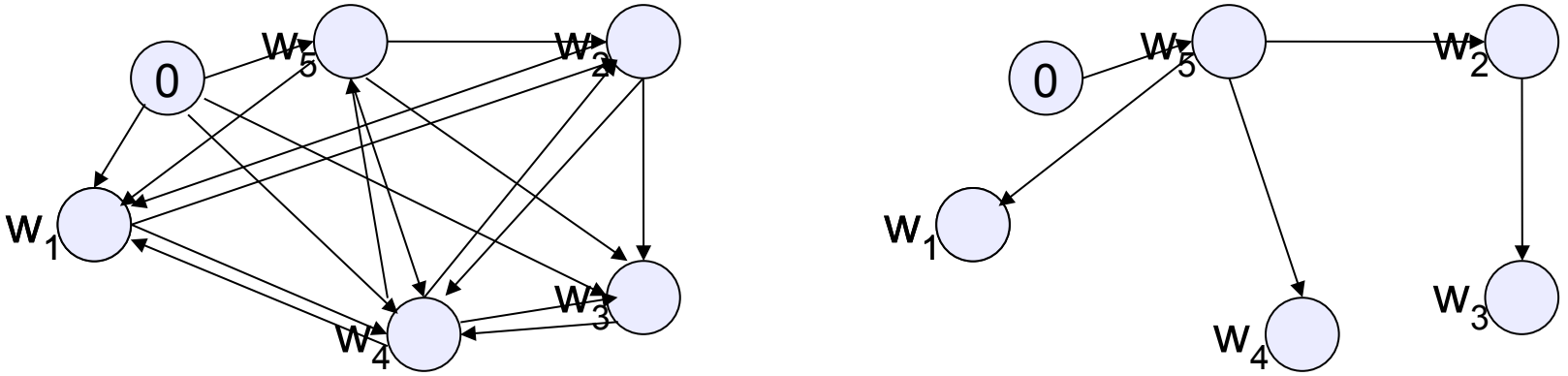
- Graph-based:

- the result is constructed in few steps (global decisions)

Graph-Based Parsing

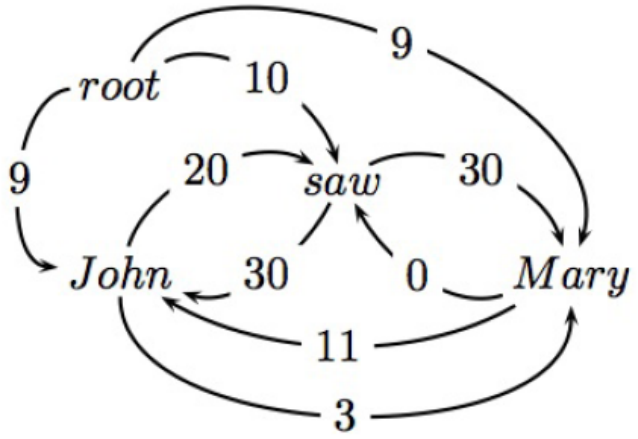
- Given the input I = w_1,w_2, . . . ,w_n, where each word corresponds to a vertex v_1, v_2, ..., v_n find a graph G= (V,A), such that G is a rooted tree and A = {<A_1,B_1>, <A_2,B_2>, ..., <A_3,B_3>} corresponds to the correct dependency tree
- Solution:

Maximum Spanning Trees

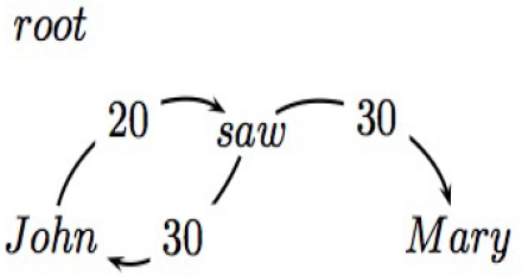


Chu-Liu-Edmonds

x = root John saw Mary



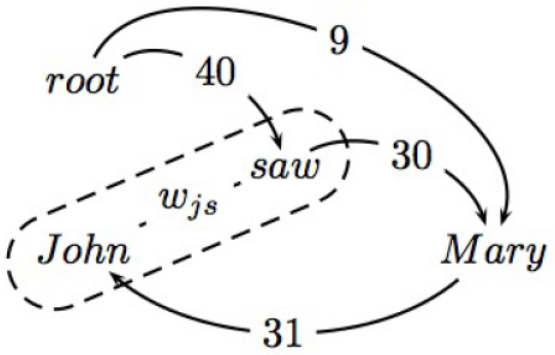
Find highest scoring incoming arc for each vertex



If this is a tree, then we have found MST!!

If not a tree, identify cycle and contract

Recalculate arc weights into and out-of cycle



Taken from Introduction to Data-Driven Dependency Parsing (Ryan McDonald, Joakim Nivre)

Edmonds Algorithm

- For all nodes (modulo root node): Choose the best incoming edge
- Repeat (greedily) until the graph contains a cycle
  - Consider each cylce as a virtual node. Compute modified edge weights for all edges which enter the cycle from outside
  - Idea: distribute (add) weights of edges of cycle to the incoming edges of the virtual node, e.g.,
    - w_n(root,saw) = w(root,saw) + w(saw,john)
    - 40 = 10 + 30

Graph-Based Parsing

- Advantages:
- State-of-the art performance
- Works well for long sentences/dependencies
- Disadvantages:
- Not incremental
- Computationally expensive
- Difficult to implement

Transition-Based Parsing

- The parse of the sentence is a sequence of operations (transitions)
- The result is a complete set of dependency pairs, which satisfy tree constraints
- An oracle tells the parser what action should be taken in every step:
- Training - use training data for simulating a perfect oracle (you have the desired result given)
- Application - use classifiers for simulating an oracle (train models, that allow the oracle to choose correct actions)

Transition System

- Given the input I = $w_1, w_2, \ldots, w_n$ perform S = $c_0, c_1, \ldots, c_n$, such that A = $\{<A_1,B_1>, <A_2,B_2>, ..., <A_3,B_3>\}$ corresponds to the correct dependency tree

Configuration – state of the parser

- Define the set of possible transitions, e.g.:
- Conditions (permissibility):

left_link(a,b) – b should not have a parent; if <A,B> is introduced to A, A should not contain a cycle etc.

- Effects:

left_link(a,b) → a becomes the parent of b

right_link(a,b) → b becomes the parent of a

shift(a,b) → move on to next pair

- Initial configuration / terminal configuration

Parsing Algorithms

- Naive:

- For every word *j* in the sentence try to combine it with other words *i* in the sentence:
- Possible operations:

  make j the parent of i

  make i the parent of j

  do not combine and j+1, i = 0

  do not combine and i+1

  - Initial state: Start with the first word
  - Terminal state: j > sentence length
- Nivre (Arc-Eager, Arc-Standard)
- Covington's parsing strategy

Naive Algorithm

c_0: j =1; i = 0, A = {}

$c_0 \rightarrow c_1$: do not combine; i+1 (j=1, i=1, A = {})

$c_1 \rightarrow c_2$: do not combine; i+1 (j=1, i=2, A = {})

$c_2 \rightarrow c_3$: make i the parent of j; (j=1, i=2, A = {<1,2>})

$c_3 \rightarrow c_4$: do not combine; i+1 (j=1, i=3, A = {<1,2>})

$c_4 \rightarrow c_5$: do not combine; i+1 (j=1, i=4, A = {<1,2>})

$c_5 \rightarrow c_6$: do not combine; j+1 (j=2, i=0, A = {<1,2>})

$c_6 \rightarrow c_7$: make i the parent of j (j=2, i=0, A = {<1,2>,<2,0>})

$c_7 \rightarrow c_8$: do not combine; i+1 (j=2, i=1, A = {<1,2>,<2,0>})

$c_8 \rightarrow c_9$: do not combine; i+1 (j=2, i=2, A = {<1,2>,<2,0>})

$c_9 \rightarrow c_{10}$: do not combine; i+1 (j=2, i=3, A = {<1,2>,<2,0>})

$c_{10} \rightarrow c_{11}$: make j the part of i (j=2, i=3, A = {<1,2>,<2,0>, <3,2>})

$c_{11} \rightarrow c_{12}$: do not combine; i+1 (j=2, i=4, A = {<1,2>,<2,0>, <3,2>})

$c_{12} \rightarrow c_{13}$: make j the part of i (j=2, i=4, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{13} \rightarrow c_{14}$: do not combine; j+1 (j=3, i=0, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{14} \rightarrow c_{15}$: do not combine;i+1 (j=3, i=1, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{15} \rightarrow c_{16}$: do not combine;i+1 (j=3, i=2, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{16} \rightarrow c_{17}$: do not combine;i+1 (j=3, i=3, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{17} \rightarrow c_{18}$: do not combine;i+1 (j=3, i=4, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{18} \rightarrow c_{19}$: do not combine; j+1 (j=4, i=0, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{19} \rightarrow c_{20}$: do not combine;i+1 (j=4, i=1, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{20} \rightarrow c_{21}$: do not combine;i+1 (j=4, i=2, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{21} \rightarrow c_{22}$: do not combine;i+1 (j=4, i=3, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{22} \rightarrow c_{23}$: do not combine;i+1 (j=4, i=4, A = {<1,2>,<2,0>, <3,2>,<4,2>})

$c_{23:}$ terminal configuration

$_0$ John$_1$ saw$_2$ Mary$_3$.$_4$

Naive Algorithm

- Obvious disadvantages:
  - Too many senseless configurations
  - $O(n^2)$ runtime (if no readings are considered)

- Advantages:
  - Simple to implement

Oracle

- Which transition to chose in which state?
- Every configuration is transformed to a feature vector:
- The history of previous transitions can be used
- Word information and context information is available
- External resources can be used

Feature Models

- Sample configuration: (j=2, i=3, A = {<1,2>,<2,0>})
- Feature templates: wf(x), pos(x), dist(x,y), isRoot(x)
- Features: wf(2)=saw, wf(3)=Mary, pos(2)=VBD, pos(3)=NNP, dist(2,3)=1, isRoot(2)=true, wf(1)=John, pos(1)=NNP
- Transition: *make j the part of i*
- For some learning approaches very complex feature engineering is required

0 John1 saw2 Mary3 .4

Learning

- Print all feature vectors into a file in format required by the machine learning method of your choice:

wfi=Mary posi=NNP wfj=saw posj=VBD link2

wfi=Mary posi=NNP wfj=John posj=NNP shift

- Or

1:1 2:1 3:1 4:1 0

1:1 2:1 5:1 6:1 1

Alphabet = (1 - wfi=Mary; 2 - posi=NNP; 3 - wfj=saw; 4 - posj=VBD; 5 - wfj=John; 6 - posj=NNP); (0 - link2, 1 - shift)

- Or Weka ARFF

Classification

- Instance: wfi=Mary posi=NNP wfj=saw posj=VBD ?
- Classes: c_1 – link(i,j), c_2 – link(j,i),c_3 – shift etc.
- Classification:
- $sum(c_1)=d_1+w_{1,c1}+w_{2,c1}+w_{3,c1}w_{n,c1}$
- $sum(c_2)=d_2+w_{1,c2}+w_{2,c2}+w_{n,c2}$
- $sum(c_3)=d_3+w_{1,c3}+w_{2,c3}+w_{n,c3}$
- Biggest $sum(c_j)$: $max = max\{sum(c_1),sum(c_2),sum(c_3)\}$
- Probability of c_j: $p(c_j)=exp(sum(c_j)-max)$
- Normalisation: $p(c_j)=$ $\frac{p(c_j)}{\sum \text{sum}\, p(c_j)}$

Classification

- sum(c_1)=1.323, sum(c_2)=-0.119, sum(c_3)=-1.204
- The maximum is obviously max=sum(c_1)=1.323
- p(c_1)=exp(sum(c_1)-max)=exp(0)=1
- p(c_2)=exp(sum(c_2)-max)=exp(-1.442)=0.236
- p(c_3)=exp(sum(c_3)-max)=exp(-2.527)=0.08
- The sum of all sum(c_j) is 1.316. Thus the normalised probability distribution is:
- p(c_1)= $\frac{1}{1.316}$ =0.76
- p(c_2)= $\frac{0.236}{1.316}$ =0.18
- p(c_3)= $\frac{0.08}{1.316}$ =0.06

Summary

- Dependency Grammar and Parsing
- Transition-based approach
  - Idea
  - Algorithms (next lecture)
- Learning and Classification
  - Idea
  - Approaches and Data (next lecture)

Exercise

- Will appear on the course page very soon