Non-projective Dependency Parsing using Spanning Tree Algorithms

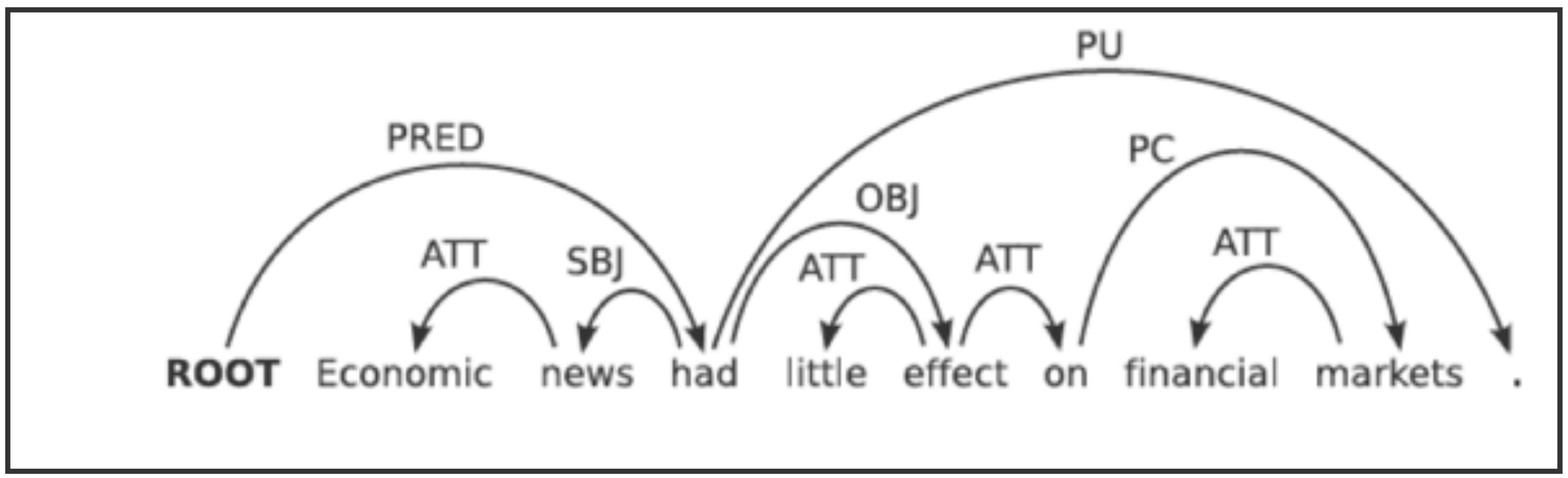
Qian Zhong

Outline

- **Basic Concepts**
- Edge-based factorization
- Parsing Algorithm & Learning Algorithm
- Experiments and Results

Recap: Dependency Parsing Basics

- **Dependency relations:** syntactic structure essentially consists of words linked by binary, asymmetrical relations



Dependency Structure of English Sentence, Figure Adapted from Dependency Parsing (Kübler et.al, 2009, p2)

Recap: Projective Trees

- If we say a tree is **projective**, we mean that if we put the words in their linear order, preceded by the root, **the edges can be drawn above the words without crossings**, or, equivalently, a word and its descendants form a contiguous substring of the sentence.

Recap: Projective vs. non-projective Dependency Trees

- Projective Dependency Trees

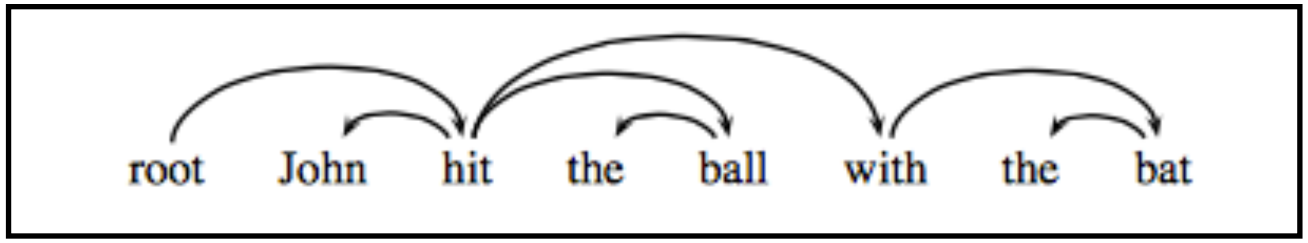


Figure A

- Non-Projective Dependency Trees

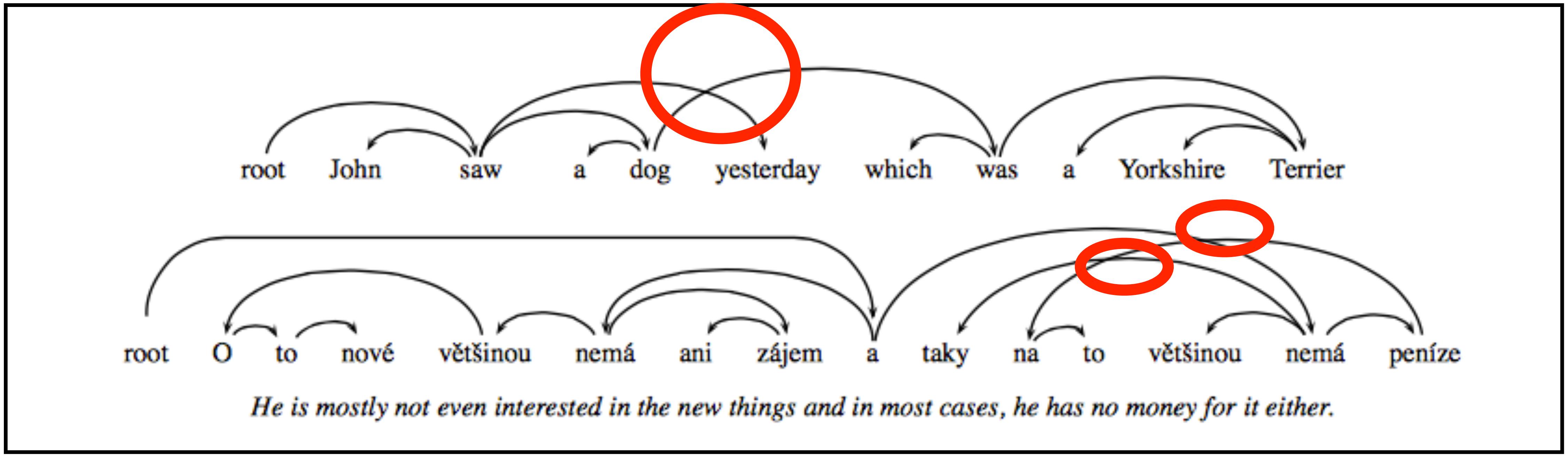


Figure B *Figures adapted from McDonald et al., 2005*

Motivation: Dependency Parsing

- More **efficient** to Learn and parse while still encoding much of the predicate-argument information needed in applications

- Applications

  Relation Extraction(Culotta and Sorensen, 2004)
  Machine Translation(Ding and Palmer, 2005)
  Synonym Generation(Shinyama et al., 2002)
  Lexical Resource Augmentation(Snow et al., 2004)

Motivation: Non-projective Trees

Why?

25% of more of the sentences in some languages cannot be given a linguistically adequate analysis without invoking non-projective structures

(Nivre, 2009; Nivre, 2006; Kuhlman and Nivre, 2006; Havelka, 2007)

In languages with more flexible word order than English, such as German, Dutch and Czech, non-projective dependencies are more frequent.

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- Basic Concepts
- **Edge-based Factorization**
- Parsing Algorithm & Learning Algorithm
- Experiments and Results

Dependency Parsing and Spanning Trees

- Edge based Factorization

Sentence:$x=x_1 \ldots x_n$

Dependency Tree y

- the set of tree edges
- $(i, j) \in y$ if there is a dependency in y from word x_i to word x_j

Score of the dependency tree

the sum of score of all the edges in the tree

Dependency Parsing and Spanning Trees

- Edge based Factorization

score of an edge: the dot product between a high dimensional feature representation of the edge and a weight vector

$$s(i, j) = w \cdot f(i, j)$$

score of a dependency tree y for sentence x:

$$s(\mathbf{x}, \mathrm{y}) = \sum_{(i,j) \in \mathrm{y}} s(i, j) = \sum_{(i,j) \in y} w \cdot f(i, j)$$

Dependency parsing: finding the dependency tree y with the **highest score** for given sentence x

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Maximum Spanning Trees: **Projective**

A Generic Directed Graph G=(V, E)

Vertex Set: $V=\{v_1, ..., v_n\}$

Set $E \subseteq [1:n]\times[1:n]$ of pairs (i, j) of directed edges vi—>vj

Score of each edge s(i, j)

G is directed, s(i, j) does not necessarily equal s(j, i)

A Maximum Spanning Tree(MST) of G is a tree y

$y \subseteq E$

that maximizes the value $\sum_{(i,j \in y)} s(i,j)$ for every vertex in V

For each sentence x, we define the directed graph

$$G_x = (V_x, E_x)$$

$$Vx = \{x_0 = root, x_1, \dots, x_n\}$$

$$E_x = \{(i,j): i \neq j, (i,j) \in [0:n]\times[1:n]\}$$

Maximum Spanning Trees: Algorithm

Chu-Liu-Edmonds(G, s)

Graph $G = (V, E)$

Edge weight function $s : E \to \mathbb{R}$

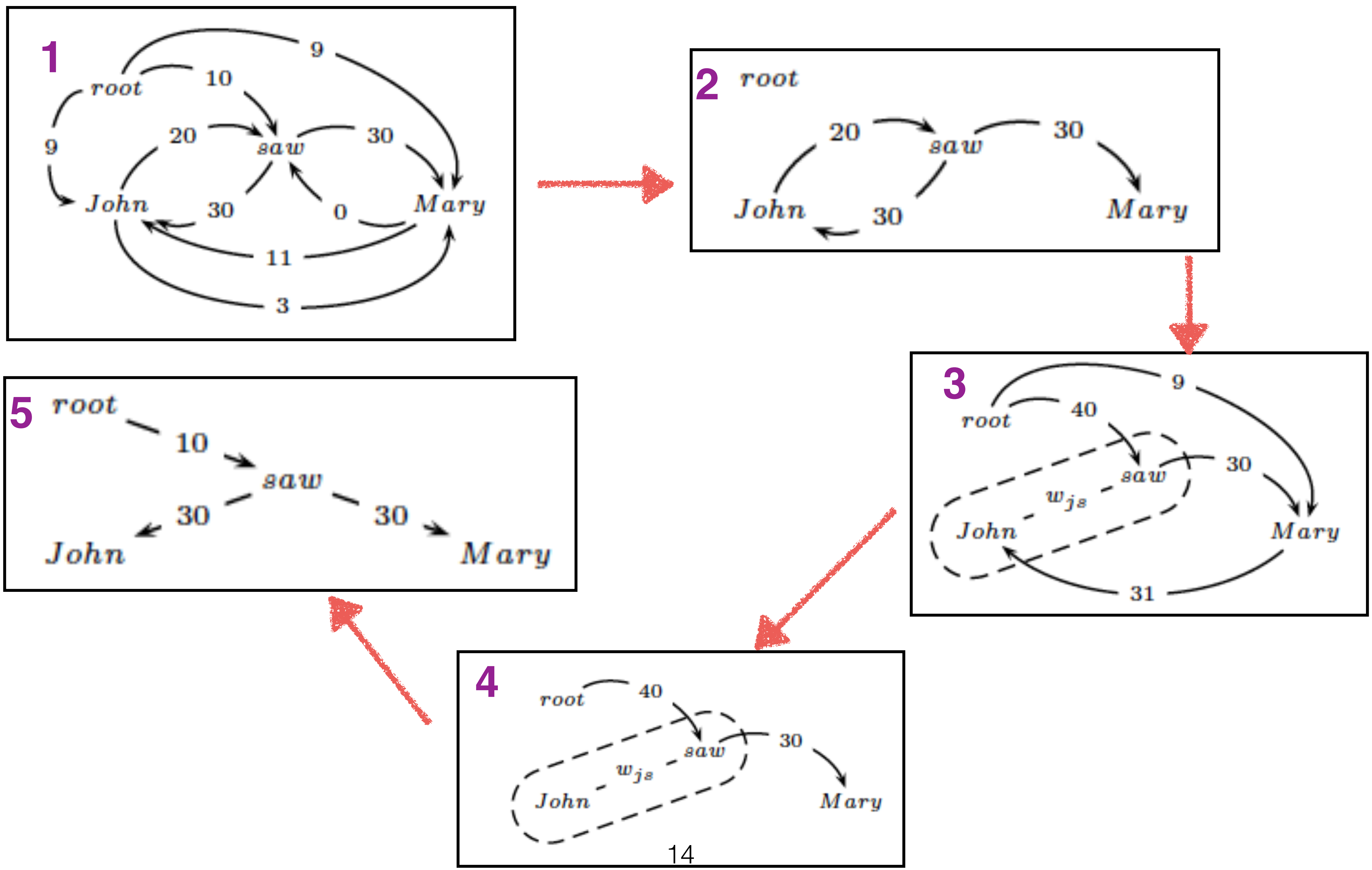
1. Let $M = \{(x^*, x) : x \in V, x^* = \arg\max_{x'} s(x', x)\}$
2. Let $G_M = (V, M)$
3. If G_M has no cycles, then it is an MST: return G_M
4. Otherwise, fi nd a cycle C in G_M
5. Let $G_C = \text{contract}(G, C, s)$
6. Let $y = \text{Chu-Liu-Edmonds}(G_C, s)$
7. Find a vertex $x \in C$ s. t. $(x', x) \in y, (x'', x) \in C$
8. return $y \cup C - \{(x'', x)\}$

contract$(G = (V, E), C, s)$

1. Let G_C be the subgraph of G excluding nodes in C
2. Add a node c to G_C representing cycle C
3. For $x \in V - C : \exists_{x' \in C}(x', x) \in E$
   Add edge (c, x) to G_C with
   $s(c, x) = \max_{x' \in C} s(x', x)$
4. For $x \in V - C : \exists_{x' \in C}(x, x') \in E$
   Add edge (x, c) to G_C with
   $s(x, c) = \max_{x' \in C} [s(x, x') - s(a(x'), x') + s(C)]$
   where $a(v)$ is the predecessor of v in C
   and $s(C) = \sum_{v \in C} s(a(v), v)$
5. return G_C

Figure 3: Chiu-Liu-Edmonds algorithm for finding maximum Spanning Trees in Directed Graph

Maximum Spanning Trees: Non-projective



Maximum Spanning Trees: projective

a dynamic programming table

C[s][t][i]

string start Ws

Root

string ends Wt

represents the value of the highest scoring projective tree that spans the string **ws . . . wt** and which is rooted at word **wi** , where **s ≤ i ≤ t**

e.g. s=0, i=0

then C[0][n][0] would represent **the value of highest scoring dependency tree** for an input sentence S = w0w1 . . . wn, which is precisely the value we are interested in for the parsing problem

Maximum Spanning Trees: projective

$$C[i][i][i] = 0.0, \text{ for all } 0 \leq i \leq n$$

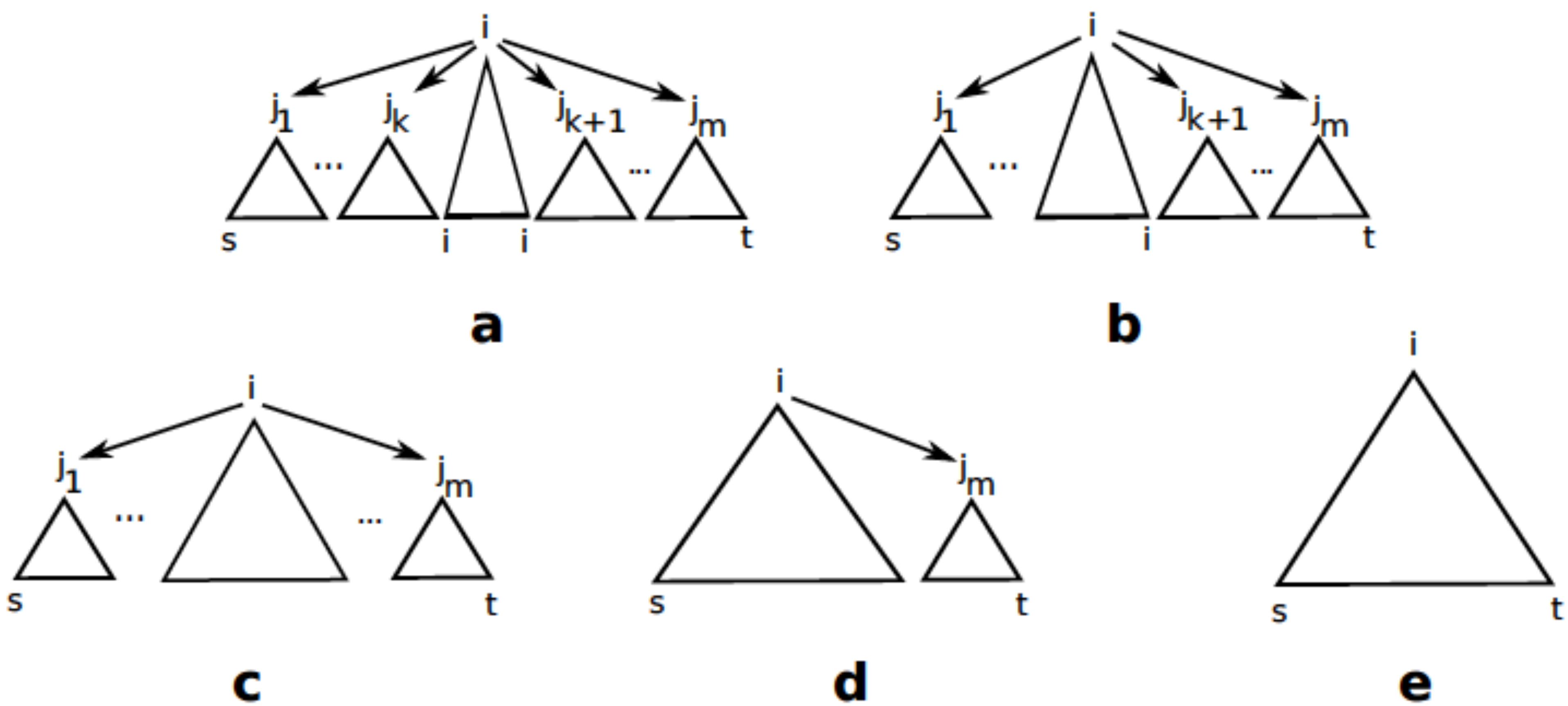


Figure 4.3: Illustration showing that every projective subgraph can be broken into a combination of smaller adjacent subgraphs.

Maximum Spanning Trees: projective

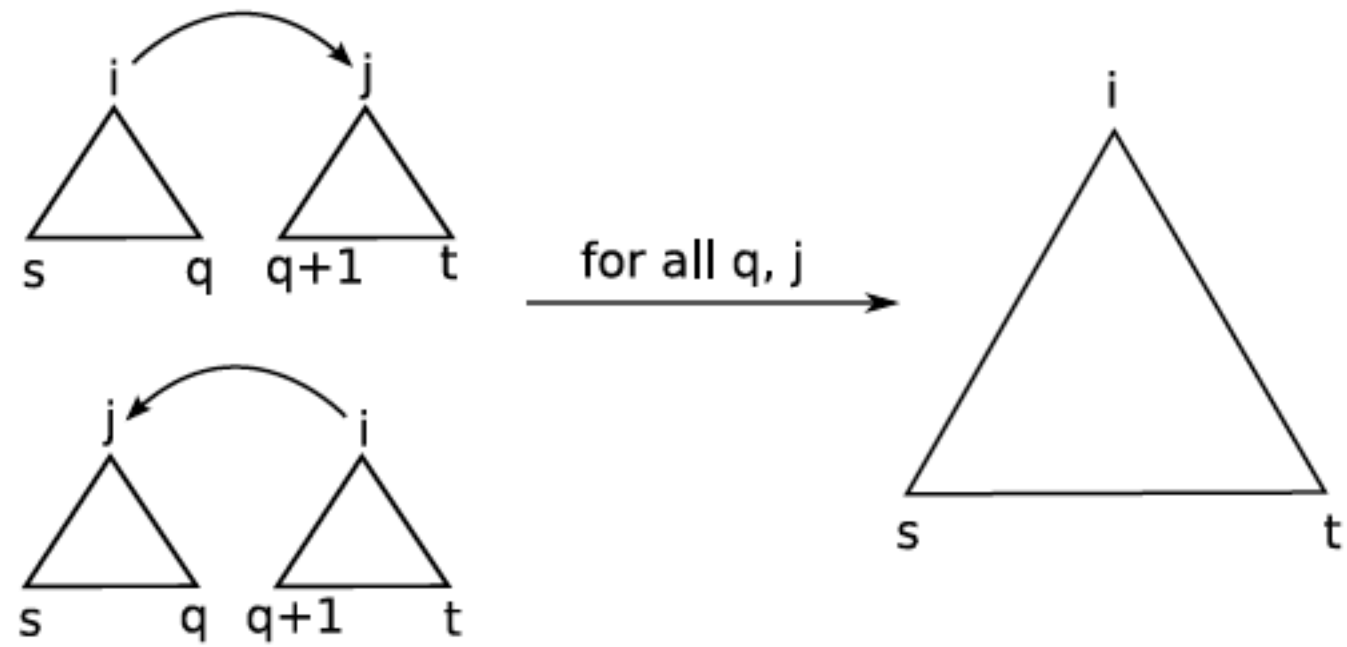


Figure 4.4: CKY algorithm for projective dependency parsing.

$$C[s][t][i] = \max_{s \le q < t, s \le j \le t} \begin{cases} C[s][q][i] + C[q+1][t][j] + \lambda_{(w_i, w_j)} & \text{if } j > i \\ C[s][q][j] + C[q+1][t][i] + \lambda_{(w_i, w_j)} & \text{if } j < i \end{cases}$$

$$A[s][t][i] = \begin{cases} A[s][q][i] \cup A[q+1][t][j] \cup (w_i, w_j) & \text{if } j > i \\ A[s][q][j] \cup A[q+1][t][i] \cup (w_i, w_j) & \text{if } j < i \end{cases}$$

The final tree for a sentence S is then G = (V ,A[0][n][0]).

Maximum Spanning Trees: projective

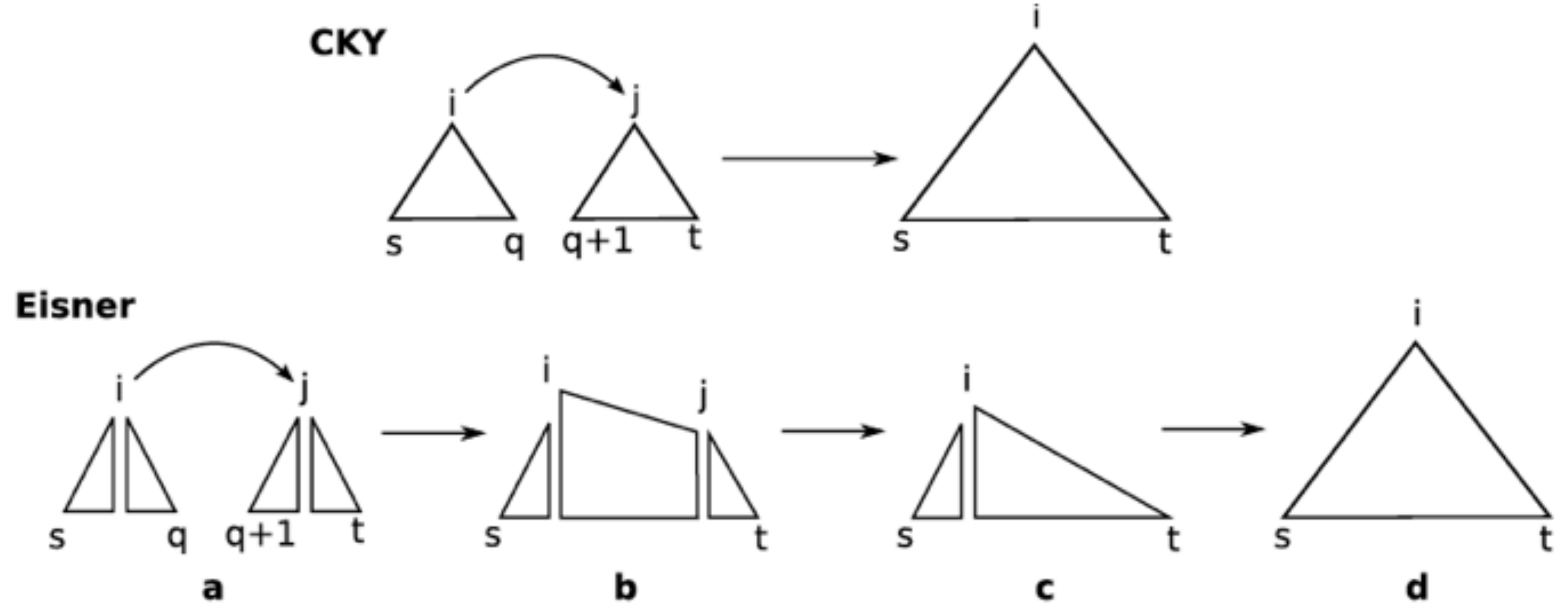


Figure 4.5: Illustration showing Eisner's projective dependency parsing algorithm relative to CKY.

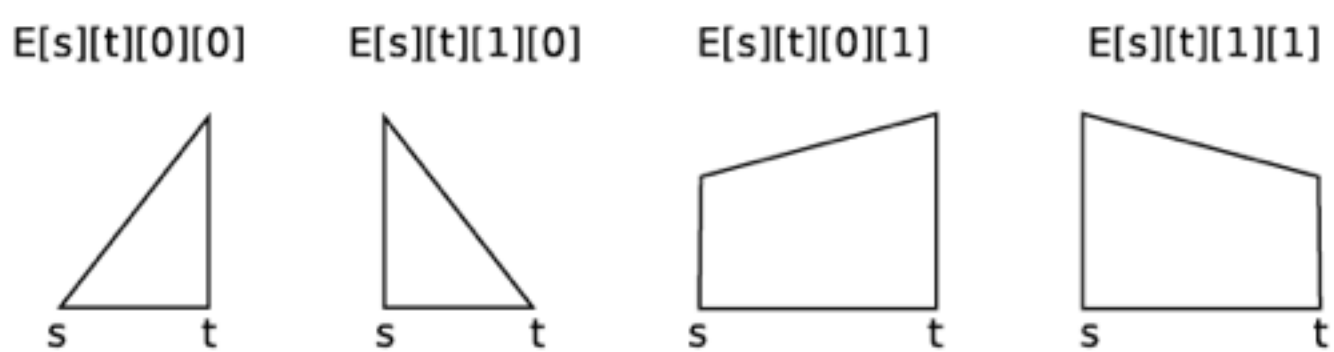


Figure 4.6: Illustration showing each type of subgraph in the dynamic program table used in Eisner's algorithm.

Maximum Spanning Trees: projective

Eisner$(S, \Gamma, \boldsymbol{\lambda})$

Sentence $S = w_0 w_1 \ldots w_n$

Arc weight parameters $\lambda_{(w_i, w_j)} \in \boldsymbol{\lambda}$

Instantiate $E[n][n][2][2] \in \mathbb{R}$

Initialization: $E[s][s][d][c] = 0.0$ for all s, d, c

for m : $1..n$

  for s : $1..n$

    $t = s + m$

    if $t > n$ then break

    % Create subgraphs with $c = 1$ by adding arcs (step a-b in figure 4.5)

    $E[s][t][0][1] = \max_{s \leq q < t} \ (E[s][q][1][0] + E[q+1][t][0][0] + \lambda_{(w_t, w_s)})$

    $E[s][t][1][1] = \max_{s \leq q < t} \ (E[s][q][1][0] + E[q+1][t][0][0] + \lambda_{(w_s, w_t)})$

    % Add corresponding left/right subgraphs (step b-c in figure 4.5)

    $E[s][t][0][0] = \max_{s \leq q < t} \ (E[s][q][0][0] + E[q][t][0][1])$

    $E[s][t][1][0] = \max_{s < q \leq t} \ (E[s][q][1][1] + E[q][t][1][0])$

Pseudo-code for Eisner's algorithm

Figure Adapted from Dependency Parsing(Kübler et.al, 2009, p53)

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Online Large Margin Learning: MIRA

Margin Infused Relaxed Algorithm (MIRA) (Crammer and Singer,2003; Crammer et al,2003)

Training data: $\mathcal{T} = \{(\boldsymbol{x}_t, \boldsymbol{y}_t)\}_{t=1}^{T}$

1. $\mathbf{w}_0 = 0;\ \mathbf{v} = 0;\ i = 0$
2. for $n : 1..N$
3. for $t : 1..T$
4. $\min \left\| \mathbf{w}^{(i+1)} - \mathbf{w}^{(i)} \right\|$

   s.t. $s(\boldsymbol{x}_t, \boldsymbol{y}_t) - s(\boldsymbol{x}_t, \boldsymbol{y}') \geq L(\boldsymbol{y}_t, \boldsymbol{y}'), \forall \boldsymbol{y}' \in \mathrm{dt}(\boldsymbol{x}_t)$
5. $\mathbf{v} = \mathbf{v} + \mathbf{w}^{(i+1)}$
6. $i = i + 1$
7. $\mathbf{w} = \mathbf{v}/(N * T)$

MIRA learning Algorithm

Online Large Margin Learning: single-best MIRA

The resulting online update

$$
\begin{aligned}
&\min \left\| \mathbf{w}^{(i+1)} - \mathbf{w}^{(i)} \right\| \\
&\text{s.t.} \quad s(\boldsymbol{x}_t, \boldsymbol{y}_t) - s(\boldsymbol{x}_t, \boldsymbol{y}') \geq L(\boldsymbol{y}_t, \boldsymbol{y}') \\
&\text{where } \boldsymbol{y}' = \arg\max_{y'} s(\boldsymbol{x}_t, \boldsymbol{y}')
\end{aligned}
$$

Related

- k highest-scoring trees with small k (McDonald et al., 2005)
- averaged perceptron algorithm(Collins, 2002) using the single highest scoring tree to update the weight vector

MIRA updates w to **maximise the margin between the corrected tree and the highest scoring tree leading to increasing accuracy**

Online Large Margin Learning: factored MIRA

Factoring the output by edges to obtain the following statements

$$\min \left\| \mathbf{w}^{(i+1)} - \mathbf{w}^{(i)} \right\|$$
$$\text{s.t. } s(l,j) - s(k,j) \geq 1$$
$$\forall (l,j) \in \boldsymbol{y}_t, (k,j) \notin \boldsymbol{y}_t$$

- the weight of the correct incoming edge to the word xj and the weight of all other incoming edges must be separated by a margin of 1

- the correct spanning tree and all incorrect spanning trees are separated by a score at least as large as the number of incorrect incoming edges.

Outline

- Basic Concepts
- Edge-based factorization
- Learning Algorithm & parsing algorithm
- **Experiments and Results**

Experiments

- Czech Prague Dependency Treebank(PDT) (Hajiˇc,1998;Hajiˇc et al.,2001)
- they used predefined training, developing and testing split of the data set
- automatically generated POS tags that are provided with the data
- features only relied on the reduced POS tag set from Collins et al. (1999)
- **23%** of the sentences in the training, development and test sets have at least one non-projective dependency
- less than **2%** of total edges are actually non-projective
- therefore, handling non-projective edges correctly have a relatively small effect on overall accuracy
- Czech A, consists of the entire PDT
- Czech B, includes only the 23% of sentences with at least one non-projective dependency

Experiments

1. **COLL1999:** The projective lexicalized phrase-structure parser of Collins et al. (1999).
2. **N&N2005:** The pseudo-projective parser of Nivre and Nilsson (2005).
3. **McD2005:** The projective parser of McDonald et al. (2005) that uses the Eisner algorithm for both training and testing. This system uses k-best MIRA with k=5.
4. **Single-best MIRA:** In this system we use the Chu-Liu-Edmonds algorithm to find the best dependency tree for Single-best MIRA training and testing.
5. **Factored MIRA:** Uses the quadratic set of constraints based on edge factorization as described in Section 3.2. We use the Chu-Liu-Edmonds algorithm to find the best tree for the test data.

Results

	Czech-A		Czech-B	
	Accuracy	**Complete**	**Accuracy**	**Complete**
COLL1999	82.8	-	-	-
N&N2005	80.0	31.8	-	-
McD2005	83.3	31.3	74.8	0.0
Single-best MIRA	84.1	32.2	81.0	**14.9**
Factored MIRA	**84.4**	**32.3**	**81.5**	14.3

Table 1: Dependency parsing results for Czech. Czech-B is the subset of Czech-A containing only sentences with at least one non-projective dependency

	English	
	Accuracy	**Complete**
McD2005	**90.9**	**37.5**
Single-best MIRA	90.2	33.2
Factored MIRA	90.2	32.3

Table 2: Dependency parsing results for English using spanning tree algorithms.

Summary

- formalize weighted dependency parsing as searching for maximum spanning trees (MSTs) in directed graphs
- Parsing Algorithm
  Non-projective: Chiu-Liu-Edmonds
  Projective: Eisner’s Algorithm
- Learning Algorithm: single/factored MIRA
- evaluated on the Prague Dependency Treebank and increasing in efficiency and accuracy

References

Kübler, S., McDonald, R., & Nivre, J. (2009). *Dependency parsing*. Synthesis Lectures on Human Language Technologies, 1(1), 1-127.

McDonald, R., Pereira, F., Ribarov, K., & Hajič, J. (2005). Non-projective dependency parsing using spanning tree algorithms. In *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing* (pp. 523-530). Association for Computational Linguistics.

Nivre, J. (2009, August). Non-projective dependency parsing in expected linear time. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP*: Volume 1-Volume 1 (pp. 351-359). Association for Computational Linguistics.

Thank you!

Any Questions?