Statistical Dependency Parsing

The State of the Art

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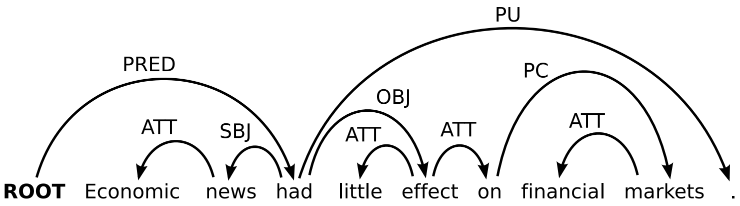
Introduction

- Syntactic parsing of natural language
  - Who does what to whom?
- Dependency-based syntactic representations
  - Long tradition in descriptive and theoretical linguistics
  - Increasingly popular in computational linguistics



Why?

- Usefulness of dependency structures in applications
  - Transparent encoding of predicate-argument structure
  - Interface from parser to downstream application
- Availability of dependency treebanks
  - Dependency annotation natural for many languages
  - Data sets from CoNLL shared tasks (2006–2009)
- Advancement of statistical dependency parsing
  - Simple and efficient parsing methods
  - High accuracy for many languages

Outline

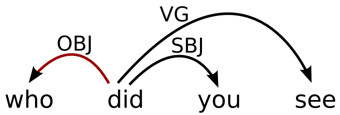
- Basic concepts
  - Representations, tasks, metrics, benchmarks
- Parsing methods
  - Chart parsing techniques
  - Parsing as constraint satisfaction
  - Transition-based parsing
  - Hybrid methods
- Future challenges
  - Where do we go from here?

Dependency Graphs

- A dependency graph for a sentence $S = w_1, \ldots, w_n$ is a directed graph $G = (V, A)$, where:
  - $V = \{1, \ldots, n\}$ is the set of nodes, representing tokens,
  - $A \subseteq V \times V$ is the set of arcs, representing dependencies.
- Note:
  - Arc $i \rightarrow j$ is a dependency with head w_i and dependent w_j
  - Arc $i \rightarrow j$ may be labeled with a dependency type $r \in R$

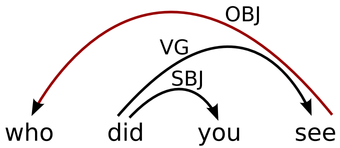
Constraints on Dependency Graphs

- *G* must be a projective tree
  - All subtrees have a contiguous yield
  - Simple conversion from/to phrase structure trees
  - Hard to represent long-distance dependencies



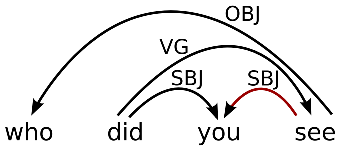
Constraints on Dependency Graphs

- *G* must be a tree
  - Subtrees may have a discontiguous yield
  - Allows non-projective arcs for long-distance dependencies
  - Prague Dependency Trebank [Hajič et al. 2001] (25% trees)



Constraints on Dependency Graphs

- G must be connected and acyclic (DAG)
  - A node may have more than one incoming arc
  - Allows multiple heads for deep syntactic relations
  - Danish Dependency Trebank [Kromann 2003]



Parsing Problem

Input: $S = w_1, \ldots, w_n$

Output: $G^* = \underset{G \in \mathcal{G}(S)}{\operatorname{argmax}} \mathcal{F}(S, G)$ $\left[\begin{array}{l} \mathcal{F}(S, G) = \text{score of } G \text{ for } S \\ \mathcal{G}(S) = \text{search space for } S \end{array} \right]$

- Parsing as an optimization problem
  - Model: Parametrized scoring function $\mathcal{F}$
  - Inference: Compute G^* given S and $\mathcal{F}$
  - Learning: Induce $\mathcal{F}$ given samples of S and G^*

Parsing Problem

Input: $S = w_1, \ldots, w_n$

Output: $G^* = (\{1, \ldots, n\}, A^*)$

- Nodes given by input, only arcs need to be found
- With tree constraint, assignment of head h_i and relation r_i

	Relation $r_i \in R$	OBJ	ROOT	SBJ	VG
Output	Head $h_i \in V \cup \{0\}$	4	0	2	2
Input	Node $i \in V$	1	2	3	4
	Word $w_i \in S$	who	did	you	see
	PoS tag	WP	VBD	PRP	VB

Evaluation Metrics

- Accuracy on individual arcs:

$$\text{Recall (R)} = \frac{|\text{PARSED} \cap \text{GOLD}|}{|\text{GOLD}|}$$

$$\text{Precision (P)} = \frac{|\text{PARSED} \cap \text{GOLD}|}{|\text{PARSED}|}$$

$$\text{Attachment score (AS)} = \text{P} = \text{R (only for trees)}$$

- All metrics can be labeled (L) or unlabeled (U)

Benchmark Data Sets

- Penn Treebank (PTB) [Marcus et al. 1993]:
  - Phrase structure annotation converted to dependencies
  - Penn2Malt – projective trees [Nivre 2006]
  - Stanford – projective trees or graphs [de Marneffe et al. 2006]
- Prague Dependency Treebank (PDT) [Hajič et al. 2001]:
  - Native dependency annotation – non-projective trees
- CoNLL Shared Tasks [Buchholz and Marsi 2006, Nivre et al. 2007]:
  - CoNLL-06: 13 languages (trees, mostly non-projective)
  - CoNLL-07: 10 languages (trees, mostly non-projective)

Parsing Methods

- Methods for statistical dependency parsing
  - Chart parsing techniques
  - Parsing as constraint satisfaction
  - Transition-based parsing
  - Hybrid methods

Chart Parsing Techniques

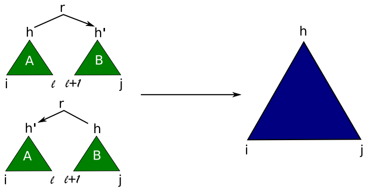
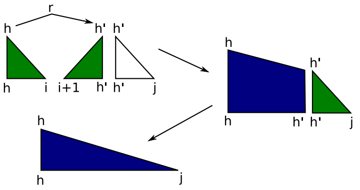
- Context-free dependency grammar:

$$H \rightarrow L_1 \cdots L_m \, h \, R_1 \cdots R_n$$

- Parsing methods:
  - Standard chart parsing techniques (CKY, Earley, etc.)
  - Goes back to the 1960s [Hays 1964, Gaifman 1965]
  - Grammar can be augmented/replaced with statistical model
  - Efficiency gains thanks to dependency tree constraints

Eisner’s Algorithm

- In standard CKY style parsing, chart items are trees
- Eisner’s algorithm [Eisner 1996, Eisner 2000]:
  - Split head representation
  - Chart items are (complete or incomplete) half-trees

<table>
<tr><th>CKY</th><th>Eisner</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>$\mathcal{C}[i, h, l, h', j] \Rightarrow O(n^5)$</td><td>$\mathcal{C}[h, h', j] \Rightarrow O(n^3)$</td></tr>
</table>

Statistical Models

- Chart parsing requires factorized scoring function $\mathcal{F}$:

$$
\begin{aligned}
T^* &= \operatorname*{argmax}_{T \in \mathcal{T}(S)} \mathcal{F}(S, T) \\
\mathcal{F}(S, T) &= \sum_{g \in T} f(S, g)
\end{aligned}
$$

- Size of subgraph g determines model complexity

Model	Subgraph	TC	PTB	Reference
1st-order		$O(n^3)$	90.9	[McDonald et al. 2005a]
2nd-order		$O(n^3)$	91.5	[McDonald and Pereira 2006]
3rd-order		$O(n^4)$	93.0	[Koo and Collins 2010]

Beyond Projective Trees

- Context-free techniques are limited to projective trees
- Extension to mildly non-projective trees:
  - Well-nested trees with gap degree 1 in $O(n^7)$ time [Kuhlmann and Satta 2009, Gómez-Rodríguez et al. 2009]
- Post-processing techniques:
  - 2nd-order model + hill-climbing [McDonald and Pereira 2006]
  - Can handle non-projective arcs as well as multiple heads
  - Top-scoring model in CoNLL-06 [MSTParser]

Parsing as Constraint Satisfaction

- Constraint dependency grammar [Maruyama 1990]:
  - Variables $h_1, \ldots, h_n$ with domain $\{0, 1, \ldots, n\}$
  - Grammar $\mathcal{G}$ = set of boolean constraints
  - Parsing = search for tree in $\{T \in \mathcal{T}(S) \,|\, \forall c \in \mathcal{G} : c(S, T)\}$
- Adding soft weighted constraints [Menzel and Schröder 1998]:

$$T^* = \operatorname*{argmax}_{T \in \mathcal{T}(S)} \prod_{c : \neg c(S,T)} f(c)$$

- Characteristics:
  - Non-projective trees easily accommodated
  - Constraints not inherently restricted to local subgraphs
  - Exact inference intractable except in restricted cases

Approaches to Inference

- Maximum spanning tree parsing [McDonald et al. 2005b]:
  - First-order model: constraints restricted to single arcs
  - T^* = maximum spanning tree in complete graph
  - Exact parsing with non-projective trees in $O(n^2)$ time
  - "An island of tractability" (D. Smith)
- Approximate inference for higher-order models:
  - Transformational search [Foth et al. 2004]
  - Gibbs sampling [Nakagawa 2007]
  - Loopy belief propagation [Smith and Eisner 2008]
  - Linear programming [Riedel and Clarke 2006, Martins et al. 2009]
  - Dual decomposition [Koo et al. 2010]

Transition-Based Approaches

- Transition-based dependency parsing:
  - Define a transition system for dependency parsing
  - Train a classifier for predicting the next transition
  - Use the classifier to do deterministic parsing
- Open source implementation:
  - MaltParser [Nivre et al. 2006]
    http://maltparser.org
- Characteristics:
  - Highly efficient – linear time complexity for projective trees
  - History-based feature models with unrestricted scope
  - Sensitive to local prediction errors and error propagation

Arc-Eager Shift-Reduce Parsing [Nivre 2003]

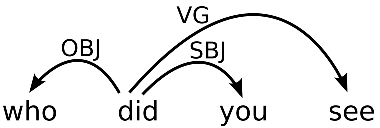
Start state: $([\,], [1, \ldots, n], \{\,\})$

Final state: $(S, [\,], A)$

Shift:	$(S, i\|B, A)$	$\Rightarrow$	$(S\|i, B, A)$
Reduce:	$(S\|i, B, A)$	$\Rightarrow$	$(S, \mathrm{B}, \mathrm{A})$
Right-Arc:	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S\|i\|j, B, A \cup \{i \rightarrow j\})$
Left-Arc:	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S, j\|B, A \cup \{i \leftarrow j\})$

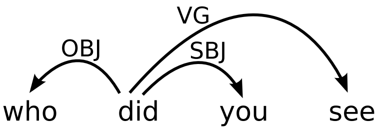
Parsing Example

Stack	**Buffer**	**Arcs**
$[\,]_S$	$[$who, did, you, see$]_B$	{ }



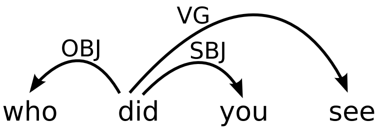
Parsing Example

Stack	Buffer	Arcs
$[\text{who}]_S$	$[\text{did, you, see}]_B$	{ }



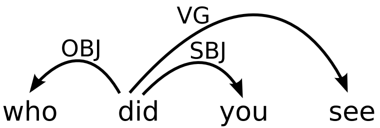
Parsing Example

Stack	Buffer	Arcs
$[\ ]_S$	$[\text{did, you, see}]_B$	$\{ \text{who} \xleftarrow{\text{OBJ}} \text{did} \}$



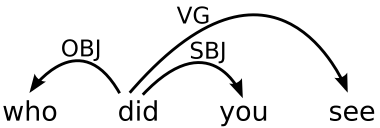
Parsing Example

Stack	**Buffer**	**Arcs**
$[\text{did}]_S$	$[\text{you, see}]_B$	$\{ \text{who} \xleftarrow{\text{OBJ}} \text{did} \}$



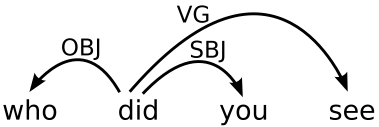
Parsing Example

Stack	Buffer	Arcs
$[\text{did}, \text{you}]_S$	$[\text{see}]_B$	$\{ \text{who} \xleftarrow{\text{OBJ}} \text{did}, \text{did} \xrightarrow{\text{SBJ}} \text{you} \}$



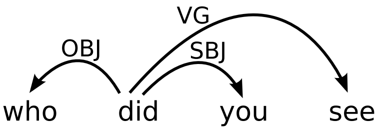
Parsing Example

Stack	**Buffer**	**Arcs**
$[\text{did}]_S$	$[\text{see}]_B$	$\{ \text{who} \xleftarrow{\text{OBJ}} \text{did}, \; \text{did} \xrightarrow{\text{SBJ}} \text{you} \}$



Parsing Example

Stack	Buffer	Arcs
$[\text{did}, \text{see}]_S$	$[\,]_B$	$\{\ \text{who} \xleftarrow{\text{OBJ}} \text{did},$ $\text{did} \xrightarrow{\text{SBJ}} \text{you},$ $\text{did} \xrightarrow{\text{VG}} \text{see}\ \}$



Statistical Models

- Parse defined by transition sequence $TS = s_0, s_1, \ldots, s_n$
- Local learning [Yamada and Matsumoto 2003, Nivre et al. 2004]:
  - Maximize accuracy of local prediction $f(s_i, s_{i+1})$
  - Deterministic parsing with 1-best configuration
  - Top-scoring model in CoNLL-06 [MaltParser]
- Global learning [Titov and Henderson 2007, Zhang and Clark 2008]:
  - Maximize accuracy over entire sequence $\sum_{i=0}^{n-1} f(s_i, s_{i+1})$
  - Beam search with k-best configurations
  - State of the art on PTB: 92.9 UAS [Zhang and Nivre 2011]

Beyond Projective Trees

- Directed acyclic graphs in linear time [Sagae and Tsujii 2008]:

  Right-Arc: $(S|i, j|B, A) \Rightarrow (S|i, j|B, A \cup \{i \rightarrow j\})$
  Left-Arc: $(S|i, j|B, A) \Rightarrow (S|i, j|B, A \cup \{i \leftarrow j\})$

- Subset of non-projective trees in linear time [Attardi 2006]:

  Right-Arc2: $(S|i|k, j|B, A) \Rightarrow (S|i|k, B, A \cup \{i \rightarrow j\})$
  Left-Arc2: $(S|i|k, j|B, A) \Rightarrow (S|k, j|B, A \cup \{i \leftarrow j\})$

- All non-projective trees in linear expected time [Nivre 2009]:

  Swap: $(S|i|k, j|B, A) \Rightarrow (S|i, j|k|B, A)$

Hybrid Methods

- Parser combination by voting:
  - Majority vote for h_i and r_i [Zeman and Žabokrtský 2005]
  - Vote for $f(S, g)$ in MST parsing [Sagae and Lavie 2006]
  - Top-ranked system in CoNLL-07 [Hall et al. 2007]
- Parser combination by stacking:
  - Let P2 learn from output of P1 [Nivre and McDonald 2008]
  - Substantial improvement for best systems in CoNLL-06 [Nivre and McDonald 2008, Torres Martins et al. 2008]
- Parser combination by dual decomposition:
  - Optimize joint score $\mathcal{F}_1(T) + \mathcal{F}_2(T)$
  - 1st-order MST + 3rd-order non-projective chart parsing
  - State of the art for PDT and CoNLL-06 [Koo et al. 2010]

Future Challenges

- Typological diversity
- Morphology and syntax
- More expressive representations
- Linguistic theory

Typological Diversity

- Parsing accuracy varies considerably across languages
  - CoNLL shared task 2007 [Nivre et al. 2007]:
    - $84 \leq \text{LAS} \leq 90$: Catalan, Chinese, English, Italian
    - $76 \leq \text{LAS} \leq 80$: Arabic, Basque, Czech, Greek, Hungarian, Turkish
  - Parsing accuracy correlated with language type
  - More configurational languages get higher accuracy
- Dependency models better suited for free word order?
  - The gap may be smaller than for phrase structure parsers
  - Statistical parsing models may be too configurational

Morphology and Syntax

- Morphological information helps syntactic parsing:
  - Experimental results for Russian [Nivre et al. 2008]:
    - Without morphology: 74.5 LAS
    - With morphology: 82.3 LAS
  - Note: Gold standard annotation as input
- Statistical dependency parsers assume tagged input
  - Morphological disambiguation prior to syntactic parsing
  - Pipeline approach may lead to error propagation
  - Experimental results for Turkish [Eryigit et al. 2008]:
    - Gold tags/morphology: 67.0 LAS
    - Automatic tags/morphology: 63.2 LAS
- Integrated morphological and syntactic processing?

More Expressive Representations

- Are projective trees sufficient?
  - Syntactic discontinuity ⇒ non-projective trees
  - Deep syntactic dependencies ⇒ multiple heads (or strata)
- Non-projective trees
  - Comparative evaluation [Kuhlmann and Nivre 2010]:
    - Pseudo-projective parsing [Nivre and Nilsson 2005]
    - Non-projective transitions [Attardi 2006]
    - Online reordering [Nivre 2009]

  Precision/Recall: Czech (80/60), English (60/50), German (70/50)
- Beyond single trees
  - Multiple heads [McDonald and Pereira 2006, Sagae and Tsujii 2008]
  - Multistratal representations?

Linguistic Theory

- Dependency parsing $\not\Rightarrow$ dependency grammar
  - Parsers have little or no notion of valency
  - Two subjects (or none) for the same verb
- Linguistic theory can help in many ways
  - Non-configurationality requires lexical information
  - Complex morphology needs paradigmatic information
  - Richer representations must be theoretically constrained
- But it must be handled with care
  - Non-local constraints may undermine efficiency
  - Hard constraints may undermine robustness

Conclusion

- We have come a long way ...
  - Robust and efficient parsing for a wide range of languages
  - Fairly accurate parsing for some languages (and domains)
- But we still have work to do ...
  - Improve parsing accuracy for richly inflected languages
  - Integrate morphological and syntactic analysis
  - Handle more expressive representations (when required)
  - Exploit the full potential of linguistic theory

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