Dependency parsing al Linguistics III (ISCL-BA-07)

Çağrı Çöltekin ccoltekin@sfs.uni-tuebingen.de

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Dependency grammars



- The structure of the sentence is represented by asymmetric, binary relations
- between syntactic units
- . Each relation defines one of the words as the head and the other as dependent
- Typically, the links (relations) have labels (dependency types)
- . Often an artificial root node is used for computational c

Dependency grammars: common assumptions

- · Every word has a single head
- The dependency graphs are acyclic
- The graph is connected
- · With these assumptions, the repr
- · Note that these assumptions are not universal but parsing

Dependency grammars

- + Close relation to semantics + Faster for flexible/free word order
- + Lots, lots of (multi-lingual) computational work, resources + Often much useful in downstream tasks
- + More efficient parsing algorithms
- No distinction between modification of head or the whole 'constituent
- Some structures are difficult to annotate, e.g., coordination

Grammar-driven dependency parsing

- · Grammar-driven dependency parsers typically based on
 - lexicalized CF parsing
 constraint satisfaction problem
 - start from fully connected graph, eliminate trees that do ne
 exact solution is intractable, often employ heuristics, appro
 sometimes 'soft', or weighted, constraints are used

 Practical implementations exist

. Our focus will be on data-driven methods

Shift-Reduce parsing → P | S + P | S − P
 → Num | P × Num | P / Num

Dependency grammars

- · Dependency grammars gained popularity in linguistics (particularly in CL) rather recently
 - * They are old: roots can be traced back to Pāṇini (approx. 5th century BCE)
 - Modern dependency grammars are often attributed to tesniere1959
 - . The main idea is canturing the relations between words rather than grouning them into (abstract) cor

Dependency grammars: alternative notation(s)



Dependency grammars: projectivity



- If a dependency graph has no crossing edges, it is said to be projective
- Non-projectivity stems from long-distance dependencies and free word order
- · Projective dependency trees can be represented with context-free grammars · In general, projective dependencies are parseable more efficiently

Dependency parsing

- * Dependency parsing has many similarities with context-free parsing (e.g.,
- It also has some differences (e.g., number of edges and depth of trees are limited) Dependency parsing can be
- grammar-driven (hand crafted rules or constraints)
 data-driven (rules/model is learned from a treebank)
- . There are two main approaches:
- Graph-based similar to context-free parsing, search for the best tree structure

Transition-based similar to shift-reduce parsing (used for programming language parsing), but using greedy search for the best transition sequence

Data-driven dependency parsing

- · Almost any modern/practical dependency parser is statist
 - . The 'grammar', and the (soft) con straints are learned from a tre
 - There are two main approaches:
 Graph-based search for the best tree structure, for example

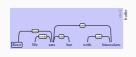
 - find minimum spanning tree (MST)
 adaptations of CF chart parser (e.g., CKY)
 - (in general, computationally more expensive sition-based similar to shift-reduce (LR(k)) parsing
 - nine an operation (shift or
 - Single pass over the sentence, det reduce) at each step
 Linear time complexity
 We need an approximate method
 - y ate method to determine the best ope

Transition-based parsing

- \star The shift-reduce (LR) parsers for formal languages are deterministic, actions are determined by a table lookup
- · Natural language sentences are ambiguous, a dependency parser's actions
- cannot be made deterministic · Operations are (somewhat) different: instead of reduce (using
- phrase-structure rules) we use arc operations connecting two words with a labeled arc
- · More operations may be defined (e.g., to deal with non-projectivity)

A typical transition system Transition based parsing $(\sigma \mid w_i)$, $w_j \mid \beta$, A . Use a stack and a buffer of unproces * Parsing as predicting a sequence of transitions like pop w_L
 add arc (w_j, r, w₁) to A (keep w_j in the buffer)
 Aac_τ: (σ | w₁, w_j | β, A) → (σ , w₁ | β, A ∪ {(w₁, r, w_j)}) pop w_L,
add arc (w_L, τ, w_J) to A,
move w_L to the buffer Sieft: $(\sigma_j, w_j \mid \beta, A) \rightarrow (\sigma \mid w_j, \beta, A)$ push w_j to the stack
 remove it from the buffer Transition based parsing: example Transition based parsing: example LEFT-ARC(NSUB) Root We saw her with binoculars Root We saw her with binoculars Transition based parsing: example Transition based parsing: example Rісит-Авс(он) Transition based parsing: example Right-Arc(ROOT)

Transition based parsing: example



The training data

 For example, Left-Arc_t if $(\beta[0], \tau, \sigma[0]) \in A$ Right-Arc_t if $(\sigma[0], \tau, \beta[0]) \in A$

Shift otherwise

Making transition decisions

- Unlike deterministic parsing (for formal languages), we cannot build a table to determinize the parser actions
- The typical method is to train a (discriminative) classifier
- Almost any machine learning (classification) method is applicable
- The features used for prediction is extracted from the states of the parser: Top-k words on the stack
 Next-m words in the buffer
 Transition decisions made so far (the arcs)
- Given these objects, one can extract and use arbitrary features:
 - Words as categorical variables
 POS tags
 - Embeddings

Non-projective parsing

- * The transition-based parsing we defined so far works only for projective dependencies
- One way to achieve (limited) non-projective parsing is to add special operations:
 - Perainten.

 Swap operation that swaps tokens in the stack and the buffer

 Lusy-Auc and Rucser-Auc transitions to/from non-top words from the stack

Pseudo-projective parsing

and all dependents of $\beta[0]$ are attached

ures for transition-based parsing have to be from pa

. The data (treebanks) need to be preprocessed for obtaining the training data

. The general idea is to construct a transition sequence by performing a 'mock parsing using treebank annotations as an 'oracle'

. There may be multiple sequences that yield the same dependency tree, this procedure defines a 'canonical' transition sequence



Transition based parsing: summary/notes

- · Linear time, greedy, projective parsing
- Can be extended to non-projective deport
- * We need some extra work for generating gold-standard to
- from treebanks * Early errors propagate, transition-based parsers make more mistakes on
- long-distance dependencies

 The greedy algorithm can be extended to beam search for better accuracy
 (still linear time complexity)

MST algorithm for dependency parsing

- . For directed graphs, there is a polynomial time algorithm that finds t minimum/maximum spanning tree (MST) of a fully connected graph (Chu-Liu-Edmonds algorithm)
- The algorithm starts with a dense/fully connected graph
- Removes edges until the resulting graph is a tree

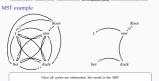
MST example For each node select the incoming arc with highest weight

MST example

Detect the cycles, con tract them to a 'single node MST example



Pick the best arc into the o



Properties of the MST parser The MST parser is non-projective

- There is an algorithm with O(n²) time complexity
- \star The time complexity increases with typed dependencies (but still close to
 - ers are associated with edges (often call The weights/pa 'arc-factored')
 - . We can learn the arc weights directly from a treebank
 - . However, it is difficult to incorporate non-local features

External features Evaluation metrics for dependency parsers Like CF parsing, exact match is often too strict
 Attachment score is the ratio of words whose heads are identified correctly
 Labelat attachment score (LAS) requires the dependency type to match
 Unfielded attachment score (UAS) disregards the dependency type For both type of parsers, one can obtain features that are based on unsupervised methods such as iffsuper voc.

— clustering
— dense vector representations (embeddings)
— alignment/transfer from bilingual corpora/treebanks — unwerner attractment score (UAS) disregards the dependency type • Precision [realit]—inseasure often used for quantifying success on identifying a particular dependency type precision is the ratio of correctly identified dependencies (of a certain type) recall is the ratio of dependencies in the gold standard that parser predicted correctly \$\frac{1}{2}\text{ \$\text{correct}\$}\text{ \$\text{correct}\$}\ easure is the harmonic mean of precision and recall (2×precision×recall) Evaluation example Dependency parsing: summary Dependency relations are often semantically easier to interpret It is also claimed that dependency parsers are more suitable for parsing free-word-order languages Dependency relations are between words, no phrases or other abstract nodes are postulated
 Two general methods: transition based greedy search, non-local features, fast, less accurate graph based exact search, local features, slower, accurate (within model limitations) Combination of different methods often result in better performs · Non-projective parsing is more difficult Most of the recent parsing research has focused on better machine learning methods (mainly using neural networks) Recallobs Reading suggestion: jurafsky2009 kubler2009 Acknowledgments, references, additional reading material