Dependency Parsing

Data structures and algorithms
for Computational Linguistics III

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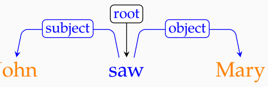
Dependency grammars

a refresher



- No constituents, units of syntactic structure are words
- 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
- The links (relations) have labels (dependency types)
- Often an artificial *root* node is used for computational convenience

Dependency grammars

common assumptions, variations

- *Single-headed*: most dependency formalisms allow a word to have a single head
- *Acyclic*: most dependency formalism do not allow loops in the graph
- *Connected*: all nodes are reachable from the 'root' node
- *Projective*: no crossing dependencies

The above assumptions (except projectivity) are common in dependency parsing.

Dependency parsing

an overview

- Dependency parsing has many similarities with context-free parsing (e.g., the result is a tree)
- They also have some different properties (e.g., number of edges and depth of trees are limited)
- The process involves discovering the relations between words in a sentence
  - Determine the head of each word
  - Determine the relation type
- Dependency parsing can be
  - grammar-driven (hand crafted rules or constraints)
  - data-driven (rules/model is learned from a treebank)

Dependency parsing

common methods for data-driven parsers

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)

Transition-based similar to shift-reduce parsing (used for programming language parsing)
- Single pass over the sentence, determine an operation (shift or reduce) at each step
- Linear time complexity
- We need an approximate method to determine the operation

Shift-Reduce parsing

a refresher through an example

Grammar

$S \rightarrow P \mid S + P \mid S - P$
$P \rightarrow \text{Num} \mid P \times \text{Num} \mid P \mathbin{/} \text{Num}$

Parser states/actions

Stack	Input buffer	Action
	$2 + 3 \times 4$	shift
2	$+ 3 \times 4$	reduce ($P \rightarrow \text{Num}$)
P	$+ 3 \times 4$	reduce ($S \rightarrow P$)
S	$+ 3 \times 4$	shift
$S +$	3×4	shift
$S + 3$	$\times 4$	reduce ($P \rightarrow \text{Num}$)
$S + P$	$\times 4$	shift
$S + P \times$	4	shift
$S + P \times 4$		reduce ($P \rightarrow P \times \text{Num}$)
$S + P$		reduce ($S \rightarrow S + P$)
S		accept

Transition-based parsing

differences from shift-reduce parsing

- The shift-reduce parsers (for programming languages) are deterministic, actions are determined by a table lookup
- Natural language sentences are ambiguous, hence 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 nodes with a label
- Further operations are often defined (e.g., to deal with non-projectivity)

Transition based parsing

- Use a *stack* and a *buffer* of unprocessed words
- Parsing as predicting a sequence of transitions like
  - LEFT-ARC: mark current word as the head of the word on top of the stack
  - RIGHT-ARC: mark current word as a dependent of the word on top of the stack
  - SHIFT: push the current word on to the stack
- Algorithm terminates when all words in the input are processed
- The transitions are not naturally deterministic, best transition is predicted using a machine learning method

(Yamada and Matsumoto 2003; Nivre, Hall, and Nilsson 2004)

A typical transition system

$$(\underbrace{\sigma \mid \overset{\text{stack top}}{w_i}}_{\text{stack}}, \underbrace{\overset{\text{next word}}{w_j} \mid \beta}_{\text{buffer}}, \underbrace{A}_{\text{arcs}})$$

LEFT-ARC$_r$: $(\sigma \mid w_i, w_j \mid \beta, A) \Rightarrow (\sigma \quad, w_j \mid \beta, A \cup \{(w_j, r, w_i)\})$

- pop w_i,
- add arc (w_j, r, w_i) to A (keep w_j in the buffer)

RIGHT-ARC$_r$: $(\sigma \mid w_i, w_j \mid \beta, A) \Rightarrow (\sigma \quad, w_i \mid \beta, A \cup \{(w_i, r, w_j)\})$

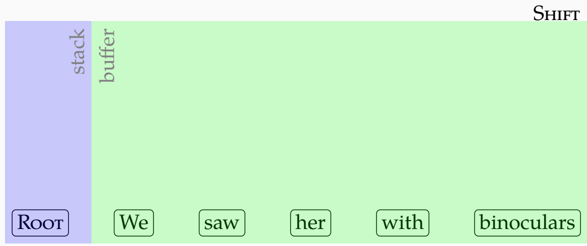
- pop w_i,
- add arc (w_i, r, w_j) to A,
- move w_i to the buffer

SHIFT: $(\sigma \quad, w_j \mid \beta, A) \Rightarrow (\sigma \mid w_j, \quad \beta, A)$

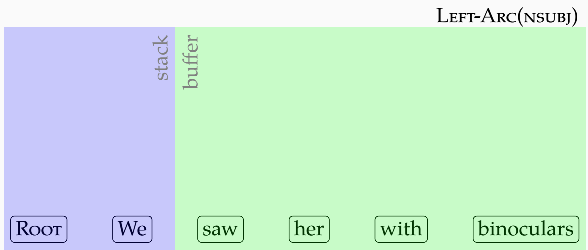
- push w_j to the stack
- remove it from the buffer

(Kübler, McDonald, and Nivre 2009, p.23)

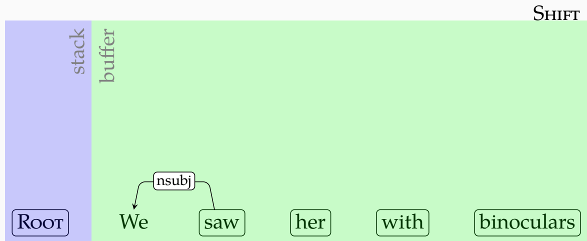
Transition based parsing: example



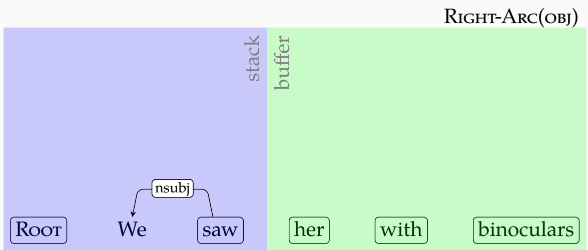
Transition based parsing: example



Transition based parsing: example

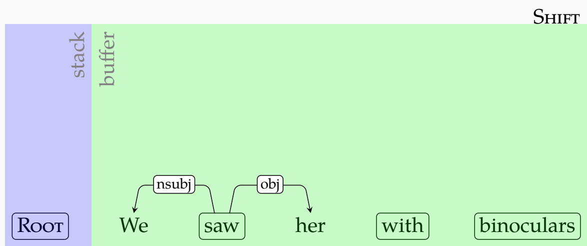


Transition based parsing: example

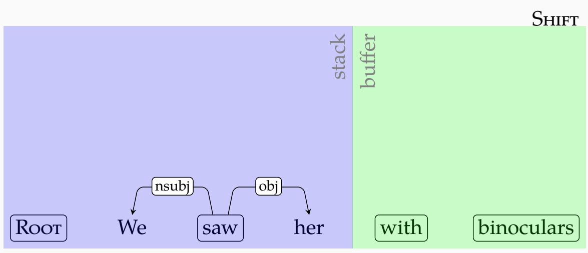


Note: We need SHIFT for NP attachment.

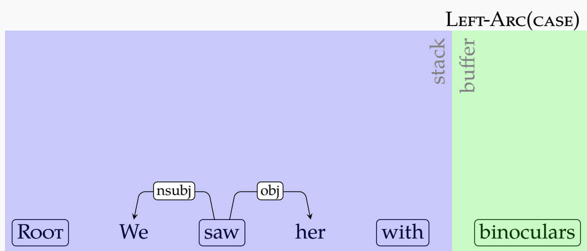
Transition based parsing: example



Transition based parsing: example

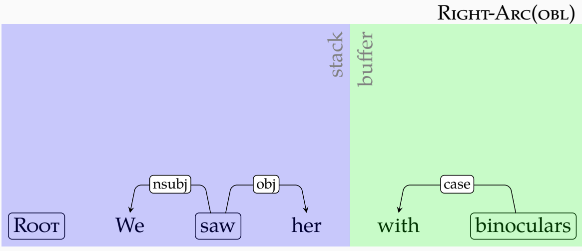


Transition based parsing: example



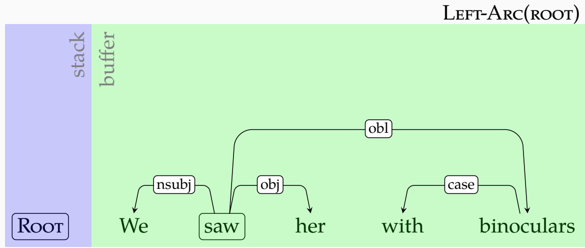
Transition based parsing: example

Right-Arc(obl)



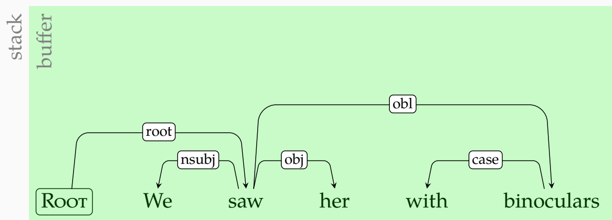
Transition based parsing: example

Left-Arc(root)

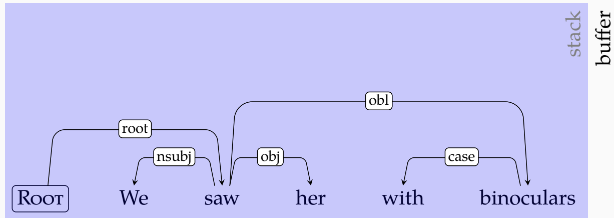


Transition based parsing: example

Shift



Transition based parsing: example



Making transition decisions

- In classical shift-reduce parsing the actions are deterministic
- In transition-based dependency parsing, we need to choose among all possible transitions
- The typical method is to train a (discriminative) classifier on features extracted from gold-standard *transition sequences*
- Almost any machine learning method method is applicable. Common choices include
  - Memory-based learning
  - Support vector machines
  - (Deep) neural networks

Features for transition-based parsing

- The features come from the parser configuration, for example
  - The word at the top of the stack, (peeking towards the bottom of the stack is also fine)
  - The first/second word on the buffer
  - Right/left dependents of the word on top of the stack/buffer
- For each possible 'address', we can make use of features like
  - Word form, lemma, POS tag, morphological features, word embeddings
  - Dependency relations – (w_i, r, w_j) triples
- Note that for some 'address'–'feature' combinations may be missing

The training data

- We want features like,
  - `lemma[Stack] = duck`
  - `POS[Stack] = NOUN`
  - ...
- But treebank gives us:

```
1   Read  read  VERB  VB  Mood=Imp|VerbForm=Fin 0 root
2   on    on    ADV   RB  _                      1 advmod
3   to    to    PART  TO  _                      4 mark
4   learn learn VERB  VB  VerbForm=Inf           1 xcomp
5   the   the   DET   DT  Definite=Def           6 det
6   facts fact  NOUN  NNS Number=Plur            4 obj
7   .     .     PUNCT .   _                      1 punct
```

- The treebank has the outcome of the parser, but none of our features.

The training data

- The features for transition-based parsing have to be from *parser configurations*
- The data (treebanks) need to be preprocessed for obtaining the training data
- Construct a transition sequence by parsing the sentences, and using treebank annotations (the set A) as an 'oracle'
- Decide for

  Left-Arc$_r$ if $(\beta[0], r, \sigma[0]) \in A$

  Right-Arc$_r$ if $(\sigma[0], r, \beta[0]) \in A$ and all dependents of $\beta[0]$ are attached

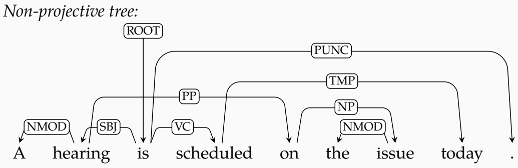
  Shift otherwise
- There may be multiple sequences that yield the same dependency tree, the above defines a 'canonical' transition sequence

Non-projective parsing

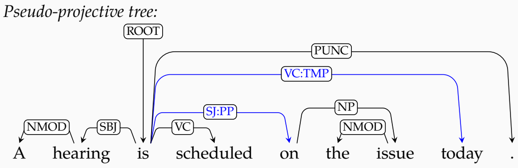
- The transition-based parsing we defined so far works only for projective dependencies
- One way to achieve (limited) non-projective parsing is to add special operations:
  - Swap operation that swaps tokens in swap and buffer
  - Left-Arc and Right-Arc transitions to/from non-top words from the stack
- Another method is pseudo-projective parsing:
  - preprocessing to 'projectivize' the trees before training
    - The idea is to attach the dependents to a higher level head that preserves projectivity, while marking it on the new dependency label
  - post-processing for restoring the projectivity after parsing
    - Re-introduce projectivity for the marked dependencies

Pseudo-projective parsing

Non-projective tree:



Pseudo-projective tree:



Transition based parsing: summary/notes

- Linear time, greedy parsing
- Can be extended to non-projective dependencies
- One can use arbitrary features,
- We need some extra work for generating gold-standard transition sequences 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)

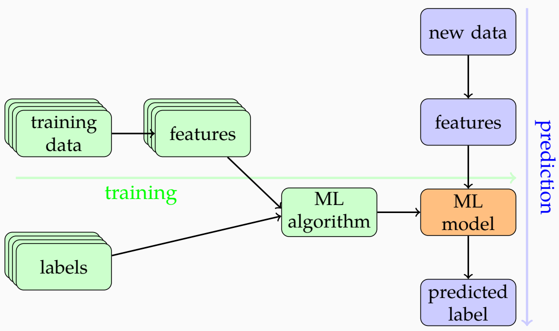
Classification

a minimal introduction

- In transition-based parsing, transition decisions come from a classifier
- At each step during parsing, we have features like
  - `form[Stack] = saw`
  - `lemma[Stack] = see`
  - `POS[Stack] = VERB`
  - `form[Buff] = her`
  - `lemma[Buff] = she`
  - `POS[Buf] = PRON`
- We need to make a transition decision such as
  - Shift
  - Right-Arc(obj)
  - Right-Arc(obl)
  - Left-Arc(acl)
- We can use any multi-class classifier, examples in the literature include
  - SVMs
  - Decision Trees
  - Neural networks
  - ...

Supervised learning

with a picture



A few notes

- In ML, the focus is generalizations outside our training data
- In this class,
  - we will treat classification methods as a black box: no introduction to any particular method
  - we will have a short, hands-on introduction to (linear) classification
- Statistical NLP course (summer semester) includes a more detailed introduction to ML methods

Graph-based parsing: preliminaries

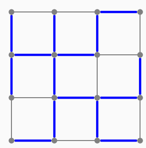
- Enumerate all possible dependency trees
- Pick the best scoring tree
- Features are based on limited parse history (like CFG parsing)
- Two well-known flavors:
  - Maximum (weight) spanning tree (MST)
  - Chart-parsing based methods

eisner1996; McDonald, Pereira, Ribarov, and Hajič 2005

MST parsing: preliminaries

Spanning tree of a graph

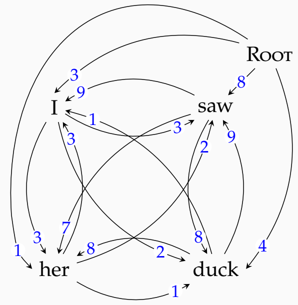
- Spanning tree of a connected graph is a sub-graph which is a tree and traverses all the nodes
- For fully-connected graphs, the number of spanning trees are exponential in the size of the graph
- The problem is well studied
- There are efficient algorithms for enumerating and finding the optimum spanning tree on weighted graphs



MST algorithm for dependency parsing

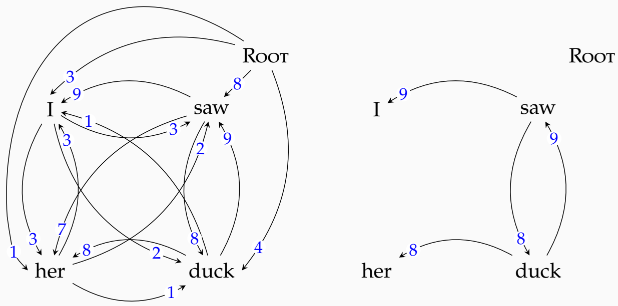
- For directed graphs, there is a polynomial time algorithm that finds the minimum/maximum spanning tree (MST) of a fully connected graph (Chu-Liu-Edmonds algorithm)
- The algorithm starts with a dense/fully connected graph
- Removes edges until the resulting graph is a tree

MST example



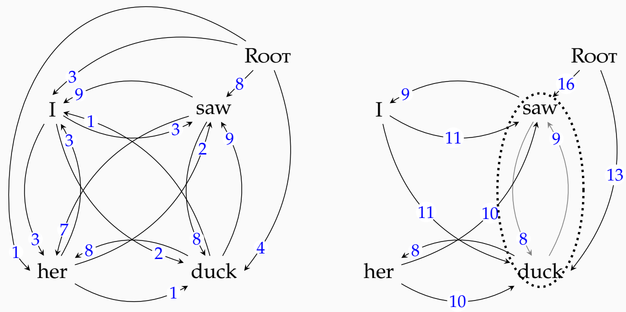
For each node select the incoming arc with highest weight

MST example



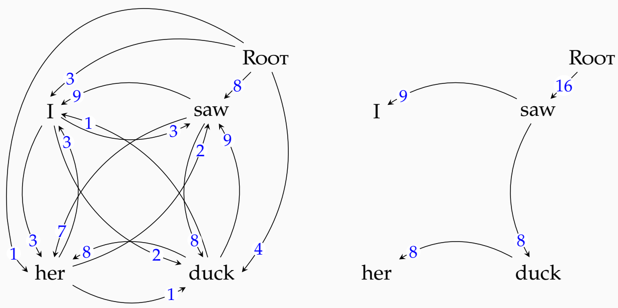
Detect the cycles, contract them to a 'single node'

MST example



Pick the best arc into the combined node, break the cycle

MST example



Once all cycles are eliminated, the result is the MST

Properties of the MST parser

- The MST parser is non-projective
- There is an algorithm with $O(n^2)$ time complexity (Tarjan 1977)
- The time complexity increases with typed dependencies (but still close to quadratic)
- The weights/parameters are associated with edges (often called 'arc-factored')
- We can learn the arc weights directly from a treebank
- However, it is difficult to incorporate non-local features

CKY for dependency parsing

- The CKY algorithm can be adapted to projective dependency parsing
- For a naive implementation the complexity increases drastically $O(n^6)$
  - Any of the words within the span can be the head
  - Inner loop has to consider all possible splits
- For projective parsing, the observation that the left and right dependents of a head are independently generated reduces the complexity to $O(n^3)$

(Eisner 1997)

Non-local features

- The graph-based dependency parsers use edge-based features
- This limits the use of more global features
- Some extensions for using 'more' global features are possible
- This often leads non-projective parsing to become intractable
- Another option is using beam search, and re-ranking based on different/global features

External features

- For both type of parsers, one can obtain features that are based on unsupervised methods such as
  - clustering
  - dense vector representations (embeddings)
  - alignment/transfer from bilingual corpora/treebanks

Errors from different parsers

- Different parsers make different errors
  - Transition based parsers do well on local arcs, worse on long-distance arcs
  - Graph based parsers tend to do better on long-distance dependencies
- Parser combination is a good way to combine the powers of different models. Two common methods
  - Majority voting: train parsers separately, use the weighted combination of their results
  - Stacking: use the output of a parser as features for another

(McDonald and Satta 2007; Sagae and Lavie 2006; Nivre and McDonald 2008)

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.
  - *Labeled attachment score* (LAS) requires the dependency type to match
  - *Unlabeled attachment score* (UAS) disregards the dependency type
- *Precision/recall/F-measure* often used for quantifying success on identifying a particular dependency type

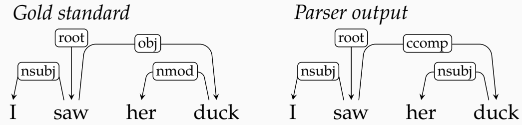
precision is the ratio of correctly identified dependencies (of a certain type)

recall is the ratio of dependencies in the gold standard that parser predicted correctly

f-measure is the harmonic mean of precision and recall $\left(\frac{2\times\text{precision}\times\text{recall}}{\text{precision}+\text{recall}}\right)$

Evaluation example

Gold standard *Parser output*



UAS	100%	
LAS	50%	
Precision$_{\texttt{nsubj}}$	50%	
Recall$_{\texttt{nsubj}}$	100%	
Precision$_{\texttt{obj}}$	0%	(assumed)
Recall$_{\texttt{obj}}$	0%	

Averaging evaluation scores

- Average scores can be

  macro-averaged over sentences

  micro-averaged over words
- Consider a two-sentence test set with

	words	correct
sentence 1	30	10
sentence 2	10	10

  - word-based average attachment score: 50% (20/40)
  - sentence-based average attachment score: 66% ((1 + 1/3)/2)

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 performance
- Non-projective parsing is more difficult
- Most of the recent parsing research has focused on better machine learning methods (mainly using neural networks)

References / additional reading material

- Kübler, McDonald, and Nivre (2009) is an accessible book on to dependency parsing
- The new version of Jurafsky and Martin (2009) also includes a draft chapter on dependency grammars and dependency parsing

References / additional reading material (cont.)

Eisner, Jason (1997). "Bilexical grammars and a cubic-time probabilistic parser". In: *Proceedings of the Fifth International Conference on Parsing Technologies (IWPT).*

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