Natural Language Processing (A brief look at CKY, and then) Dependency parsing

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Credit to Yulia Tsvetkov for slides

Announcement(s)

• A3 is out on gitlab!

The CKY algorithm for parsing with PCFGs

Parsing

- Parsing is search through the space of all possible parses
 - e.g., we may want either any parse, all parses or the highest scoring parse (if PCFG):

$\underset{T \in G(x)}{\operatorname{arg max}} P(T)$

- Bottom-up:
 - \circ $\,$ One starts from words and attempt to construct the full tree $\,$

- Top-down
 - Start from the start symbol and attempt to expand to get the sentence

CKY algorithm (aka CYK)

- Cocke-Kasami-Younger algorithm
 - Independently discovered in late 60s / early 70s

- An efficient bottom up parsing algorithm for (P)CFGs
 - can be used both for the recognition and parsing problems
 - Very important in NLP (and beyond)

• We will start with the non-probabilistic version

Constraints on the grammar

• The basic CKY algorithm supports only rules in the Chomsky Normal Form (CNF):



Constraints on the grammar

• The basic CKY algorithm supports only rules in the Chomsky Normal Form (CNF):

 $C \to x$ $C \to C_1 C_2$

- Any CFG can be converted to an equivalent CNF
 - Equivalent means that they define the same language
 - However (syntactic) trees will look differently
 - It is possible to address it by defining such transformations that allows for easy reverse transformation

Transformation to CNF form

• What one need to do to convert to CNF form

- Get rid of rules that mix terminals and non-terminals
- Get rid of unary rules:
- Get rid of N-ary rules:

 $C \to C_1$

8

 $C \to C_1 \ C_2 \dots C_n \ (n > 2)$

Crucial to process them, as required for efficient parsing

• Consider $NP \rightarrow DT NNP VBG NN$



• How do we get a set of binary rules which are equivalent?

9



 How do we get a set of binary rules which are equivalent? *NP* → *DT X X* → *NNP Y Y* → *VBG NN*

10



• How do we get a set of binary rules which are equivalent?

 $NP \to DT \ X$ $X \to NNP \ Y$ $Y \to VBG \ NN$

 A more systematic way to refer to new non-terminals *NP* → *DT* @*NP*|*DT* @*NP*|*DT* → *NNP* @*NP*|*DT*_*NNP* @*NP*|*DT*_*NNP* → *VBG NN*

• Instead of binarizing tuples we can binarize trees on preprocessing:



CKY: Parsing task

- We are given
 - \circ a grammar <N, T, S, R>
 - \circ a sequence of words

$$\boldsymbol{w} = (w_1, w_2, \dots, w_n)$$

• Our goal is to produce a parse tree for w

CKY: Parsing task

- We a given
 - \circ a grammar < N, T, S, R>

$$\circ$$
 a sequence of words $oldsymbol{w} = (w_1, w_2, \dots, w_n)$

- Our goal is to produce a parse tree for w
- We need an easy way to refer to substrings of w



Parsing one word



Wi

15

Parsing one word



16

Parsing one word



 $C \to w_i$

covers all words between *i* – 1 and *i*

Parsing longer spans

$C \rightarrow C_1 \ C_2$

Check through all C1, C2, mid



covers all wordscovers all wordsbtw min and midbtw mid and max

Parsing longer spans



covers all wordscovers all wordsbtw min and midbtw mid and max

 $C \rightarrow C_1 \ C_2$

Check through all C1, C2, mid

Parsing longer spans



covers all words between *min* and *max*

20

lead can poison						$VP \to M \ V$ $VP \to V$	nner ules
0 1 2 0	max = 1	max = 2	max = 3			$NP \to N$ $NP \to N NP$	
min = 0			S?			N ightarrow can N ightarrow lead N ightarrow poison	
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lead can poison			$VP \to M \ V$ $VP \to V$	iner lles
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P LD	$V \rightarrow poison$ $V \rightarrow lead$	³ _N , _V NP, VP			min = 2			





	$VP \rightarrow M V$				poison	can	lead	
lnner rules	$VP \rightarrow V$			3	2 3		1	 0
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$S \rightarrow NP \ VP$

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	min = 1		² N, M NP	⁵ <i>S</i> , <i>VP</i> , <i>NP</i>	$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	eterminal
	min = 2			³ N, V NP, VP	$\left \begin{array}{c} V \to poison \\ V \to lead \end{array} \right $	A D















Ambiguity





No subject-verb agreement, and *poison* used as an intransitive verb

Dependency parsing

Dependency representation



Dependency trees

- Nodes are words (along with part-of-speech tags)
- Directed arcs encode syntactic dependencies between them
- Labels are types of relations between the words
 - poss possessive
 - dobj direct object
 - nsub subject
 - det determiner



Recovering shallow semantics



- Some semantic information can be (approximately) derived from syntactic information
 - Subjects (nsubj) are (often) agents ("initiator / doers for an action")
 - Direct objects (dobj) are (often) patients ("affected entities")

Recovering shallow semantics



- Some semantic information can be (approximately) derived from syntactic information
 - Subjects (nsubj) are (often) agents ("initiator / doers for an action")
 - Direct objects (dobj) are (often) patients ("affected entities")
- But even for agents and patients consider:
 - Mary is baking a cake in the oven
 - A cake is baking in the oven
- In general it is not trivial even for the most shallow forms of semantics
 - E.g., consider prepositions: *in* can encode direction, position, temporal information, ...

Constituent and dependency representations

• Constituent trees can (potentially) be converted to dependency trees



• Dependency trees can (potentially) be converted to constituent trees



Dependency representation

- A dependency structure can be defined as a directed graph G, consisting of
 - a set V of nodes vertices, words, punctuation, morphemes
 - a set A of arcs directed edges,
 - a linear precedence order < on V (word order).
- Labeled graphs
 - nodes in V are labeled with word forms (and annotation).
 - arcs in A are labeled with dependency types
 - $L = \{l_1, \ldots, l_{|L|}\}$ is the set of permissible arc labels;
 - Every arc in A is a triple (i,j,k), representing a dependency from w_i to w_j with label l_k .



Conversion from constituency to dependency

- Xia and Palmer (2001)
 - mark the head child of each node in a phrase structure, using the appropriate head rules
 - o make the head of each non-head child depend on the head of the head-child



Figure 10.11 A lexicalized tree from Collins (1999).

Dependency vs Constituency

- Dependency structures explicitly represent
 - head-dependent relations (directed arcs),
 - functional categories (arc labels)
 - possibly some structural categories (parts of speech)

- Phrase (aka constituent) structures explicitly represent
 - phrases (nonterminal nodes),
 - structural categories (nonterminal labels)

Dependency vs Constituency trees





Parsing Languages with Flexible Word Order

Я предпочитаю утренний перелет через Денвер

I prefer the morning flight through Denver

Languages with free word order

Я предпочитаю утренний перелет через Денвер Я предпочитаю через Денвер утренний перелет Утренний перелет я предпочитаю через Денвер Перелет утренний я предпочитаю через Денвер Через Денвер я предпочитаю утренний перелет Я через Денвер предпочитаю утренний перелет

I prefer the morning flight through Denver

Dependency relations



Types of relationships

- The clausal relations NSUBJ and DOBJ identify the arguments: the subject and direct object of the predicate *cancel*
- The NMOD, DET, and CASE relations denote modifiers of the nouns flights and *Houston*.



Grammatical functions

Clausal Argument Relations	Description		
NSUBJ	Nominal subject		
DOBJ	Direct object		
IOBJ	Indirect object		
ССОМР	Clausal complement		
ХСОМР	Open clausal complement		
Nominal Modifier Relations	Description		
NMOD	Nominal modifier		
AMOD	Adjectival modifier		
NUMMOD	Numeric modifier		
APPOS	Appositional modifier		
DET	Determiner		
CASE	Prepositions, postpositions and other case markers		
Other Notable Relations	Description		
CONJ	Conjunct		
СС	Coordinating conjunction		
Figure 13.2 Selected dependence	cy relations from the Universal Dependency set. (de Marn-		

Figure 13.2 Selected dependency relations from the Universal Dependency set. (de Marneffe et al., 2014)

Dependency Constraints

- Syntactic structure is complete (connectedness)
 - o connectedness can be enforced by adding a special root node
- Syntactic structure is hierarchical (acyclicity)
 - there is a unique pass from the root to each vertex
- Every word has at most one syntactic head (single-head constraint)
 - except root that does not have incoming arcs

This makes the dependencies a tree



Projectivity

- Projective parse
 - o arcs don't cross each other
 - mostly true for English
- Non-projective structures are needed to account for
 - long-distance dependencies
 - flexible word order



Projectivity

- Dependency grammars do not normally assume that all dependency-trees are projective, because some linguistic phenomena can only be achieved using non-projective trees.
- But a lot of parsers assume that the output trees are projective
- Reasons
 - conversion from constituency to dependency
 - the most widely used families of parsing algorithms impose projectivity

Non-Projective Statistics

Arabic: 11.2 % Bulgarian: 5.4 % Chinese: 0.0 % Czech: 23.2 % Danish: 15.6 % Dutch: 36.4 % German: 27.8 % Japanese: 5.3 % Polish: 18.9 % Slovene: 22.2 % Spanish 1.7 % Swedish: 9.8 % Turkish: 11.6 % English: 0.0% (SD: 0.1%)

Percentage of non-projective trees for some treebanks of the CoNLL-X Shared Task and English.

Parsing problem

The parsing problem for a dependency parser is to find the optimal dependency tree \mathbf{y} given an input sentence \mathbf{x}

This amounts to assigning a syntactic head iand a label I to every node j corresponding to a word x_j in such a way that the resulting graph is a tree rooted at the node 0

Parsing problem

• This is equivalent to finding a spanning tree in the complete graph containing all possible arcs



Parsing algorithms

- Transition based
 - o greedy choice of local transitions guided by a good classifier
 - \circ deterministic
 - MaltParser (<u>Nivre et al. 2008</u>)
- Graph based
 - Minimum Spanning Tree for a sentence
 - McDonald et al.'s (2005) MSTParser
 - Martins et al.'s (2009) Turbo Parser

Transition Based Parsing

- greedy discriminative dependency parser
- motivated by a stack-based approach called **shift-reduce parsing** originally developed for analyzing programming languages (Aho & Ullman, 1972).
- Nivre 2003



Configuration



$$C = (\sigma, \beta, A)$$

Figure 13.5 Basic transition-based parser. The parser examines the top two elements of the stack and selects an action based on consulting an oracle that examines the current configuration.

Configuration



Operations



Operations



Operations



Shift-Reduce Parsing

Configuration:

• Stack, Buffer, Oracle, Set of dependency relations

Operations by a classifier at each step:

- Shift
 - remove w1 from the buffer, push it onto the stack as s1
- LeftArc or Reduce left
 - assert a head-dependent relation between s1 and s2 (s1 \rightarrow s2)
 - pop s1 from the stack; pop s2 from the stack; then push (s2 \leftarrow s1) onto the stack
- RightArc or Reduce right
 - assert a head-dependent relation between s2 and s1 (s2 \rightarrow s1)
 - pop s1 from the stack; pop s2 from the stack; then push $(s2 \rightarrow s1)$ onto the stack

Want to see an example of transition-based parsing in action?

Slides 30-44 of <u>this slide deck</u> by Noah Smith do a really nice job of walking through the full transition-based assembly of a sentence's parse visually.