Dependency Grammar

Introduction

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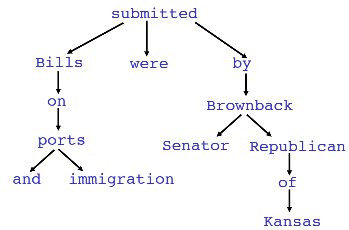
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations (“arrows”) called dependencies



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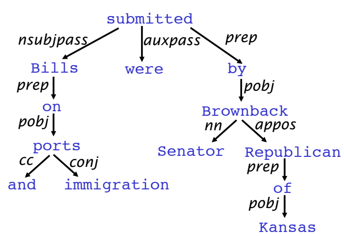
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations (“arrows”) called dependencies

The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc.)



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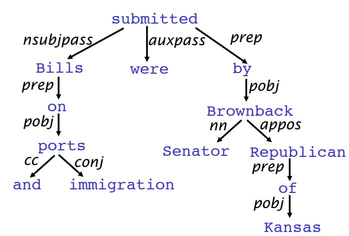
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations (“arrows”) called dependencies

The arrow connects a head (governor, superior, regent) with a dependent (modifier, inferior, subordinate)

Usually, dependencies form a tree (connected, acyclic, single-head)



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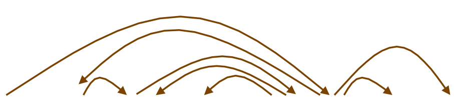
Dependency Grammar and Dependency Structure



ROOT Discussion of the outstanding issues was completed .

- Some people draw the arrows one way; some the other way!
  - Tesnière had them point from head to dependent…
- Usually add a fake ROOT so every word is a dependent of precisely 1 other node

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Dependency Grammar/Parsing History

- The idea of dependency structure goes back a long way
  - To Pāṇini’s grammar (c. 5th century BCE)
  - Basic approach of 1st millennium Arabic grammarians
- Constituency is a new-fangled invention
  - 20th century invention (R.S. Wells, 1947)
- Modern dependency work often linked to work of L. Tesnière (1959)
  - Was dominant approach in “East” (Russia, China, …)
    - Good for free-er word order languages
- Among the earliest kinds of parsers in NLP, even in the US:
  - David Hays, one of the founders of U.S. computational linguistics, built early (first?) dependency parser (Hays 1962)

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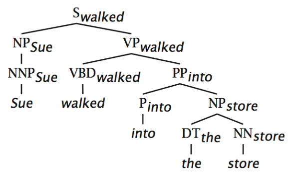
Relation between phrase structure and dependency structure

- A dependency grammar has a notion of a head. Officially, CFGs don't.
- But modern linguistic theory and all modern statistical parsers (Charniak, Collins, Stanford, …) do, via hand-written phrasal "head rules":
  - The head of a Noun Phrase is a noun/number/adj/…
  - The head of a Verb Phrase is a verb/modal/….
- The head rules can be used to extract a dependency parse from a CFG parse

- The closure of dependencies give constituency from a dependency tree
- But the dependents of a word must be at the same level (i.e., "flat") – there can be no VP!



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Dependency Conditioning Preferences

What are the sources of information for dependency parsing?

1. Bilexical affinities [issues → the] is plausible
2. Dependency distance mostly with nearby words
3. Intervening material
   Dependencies rarely span intervening verbs or punctuation
4. Valency of heads
   How many dependents on which side are usual for a head?

ROOT Discussion of the outstanding issues was completed .

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Dependency Parsing

- A sentence is parsed by choosing for each word what other word (including ROOT) that it is a dependent of.
- Usually some constraints:
  - Only one word is a dependent of ROOT
  - Don't want cycles A → B, B → A
- This makes the dependencies a tree
- Final issue is whether arrows can cross (non-projective) or not

ROOT I 'll give a talk tomorrow on bootstrapping

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Methods of Dependency Parsing

1. Dynamic programming (like in the CKY algorithm)
   You can do it similarly to lexicalized PCFG parsing: an $O(n^5)$ algorithm
   Eisner (1996) gives a clever algorithm that reduces the complexity to $O(n^3)$, by producing parse items with heads at the ends rather than in the middle
2. Graph algorithms
   You create a Minimum Spanning Tree for a sentence
   McDonald et al.'s (2005) MSTParser scores dependencies independently using a ML classifier (he uses MIRA, for online learning, but it could be something else)
3. Constraint Satisfaction
   Edges are eliminated that don't satisfy hard constraints. Karlsson (1990), etc.
4. "Deterministic parsing"
   Greedy choice of attachments guided by good machine learning classifiers
   MaltParser (Nivre et al. 2008)

DP for generative dependency grammars

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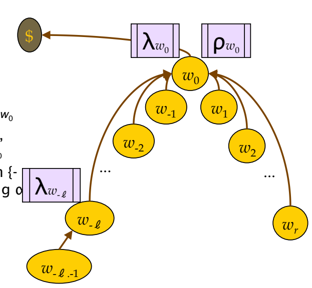
Probabilistic dependency grammar: generative model

1. Start with left wall \$
2. Generate root w_0
3. Generate left children w_{-1}, w_{-2}, ..., $w_{-\ell}$ from the FSA λ_{w_0}
4. Generate right children w_1, w_2, ..., w_r from the FSA ρ_{w_0}
5. Recurse on each w_i for i in {-ℓ, ..., -1, 1, ..., r}, sampling o (steps 2-4)
6. Return $\alpha_{\ell}\ldots\alpha_{-1}w_0\alpha_1\ldots\alpha_r$



These 5 slides are based on slides by Jason Eisner and Noah Smith

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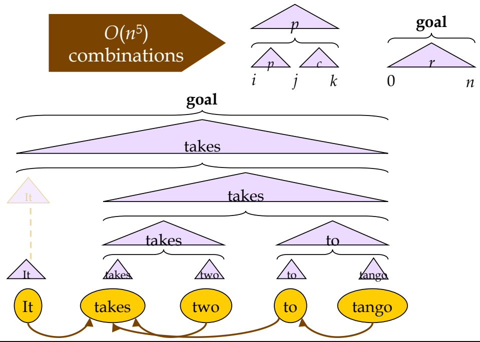
Naïve Recognition/Parsing



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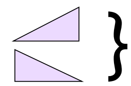
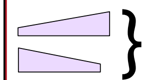
Dependency Grammar Cubic Recognition/Parsing (Eisner & Satta, 1999)



- ***Triangles***: span over words, where tall side of triangle is the head, other side is dependent, and no non-head words expecting more dependents



- ***Trapezoids***: span over words, where larger side is head, smaller side is dependent, and smaller side is still looking for dependents on its side of the trapezoid

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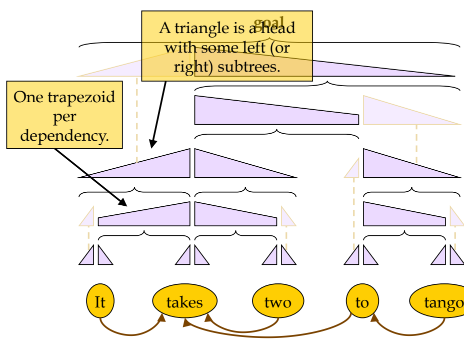
Dependency Grammar Cubic Recognition/Parsing (Eisner & Satta, 1999)



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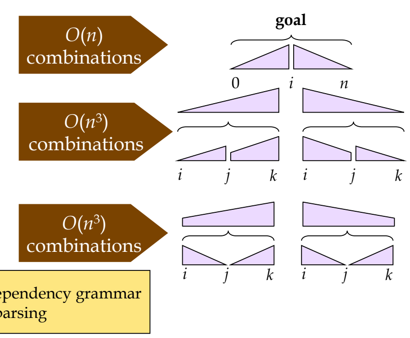
Cubic Recognition/Parsing (Eisner & Satta, 1999)



Graph Algorithms: MSTs

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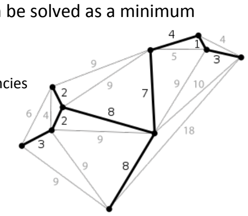
McDonald et al. (2005 ACL)

Online Large-Margin Training of Dependency Parsers

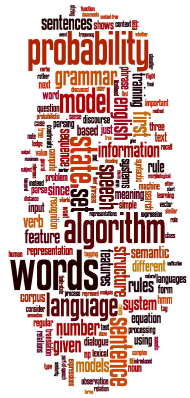
- One of two best-known recent dependency parsers
- Score of a dependency tree = sum of scores of dependencies
- Scores are independent of other dependencies
- If scores are available, parsing can be solved as a minimum spanning tree problem
  - Chiu-Liu-Edmonds algorithm
  - One then needs a score for dependencies



McDonald et al. (2005 ACL):

Online Large-Margin Training of Dependency Parsers

- Edge scoring is via a discriminative classifier
  - Can condition on rich features in that context
  - Each dependency is a linear function of features times weights
- Feature weights were learned by MIRA, an online large-margin algorithm
  - But you could use an SVM, maxent, or a perceptron
- Features cover:
  - Head and dependent word and POS separately
  - Head and dependent word and POS bigram features
  - Words between head and dependent
  - Length and direction of dependency



Greedy Transition-Based Parsing

MaltParser

MaltParser

[Nivre et al. 2008]

- A simple form of greedy discriminative dependency parser
- The parser does a sequence of bottom up actions
  - Roughly like "shift" or "reduce" in a shift-reduce parser, but the "reduce" actions are specialized to create dependencies with head on left or right
- The parser has:
  - a stack σ, written with top to the right
    - which starts with the ROOT symbol
  - a buffer β, written with top to the left
    - which starts with the input sentence
  - a set of dependency arcs A
    - which starts off empty
  - a set of actions

Basic transition-based dependency parser

Start: $\sigma = [\text{ROOT}]$, $\beta = w_1, \ldots, w_n$, $A = \varnothing$

1. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$
2. Left-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
3. Right-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_i|\beta, A \cup \{r(w_i,w_j)\}$

Finish: $\beta = \varnothing$

Notes:

- Unlike the regular presentation of the CFG reduce step, dependencies combine one thing from each of stack and buffer

Actions ("arc-eager" dependency parser)

Start: $\sigma = [\text{ROOT}]$, $\beta = w_1, \ldots, w_n$, $A = \varnothing$

1. Left-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $r'(w_k, w_i) \notin A$, $w_i \neq \text{ROOT}$
2. Right-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\quad \sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $r'(w_k, w_i) \in A$
4. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$

Finish: $\beta = \varnothing$

This is the common "arc-eager" variant: a head can immediately take a right dependent, before *its* dependents are found

Example

1. Left-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A$, $w_i \neq \text{ROOT}$
2. Right-Arc$_r$ $\quad \sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\quad \sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\quad \sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$

Happy children like to play with their friends .

	[ROOT]	[Happy, children, …]	$\varnothing$
Shift	[ROOT, Happy]	[children, like, …]	$\varnothing$
LA$_{amod}$	[ROOT]	[children, like, …]	{amod(children, happy)} = A_1
Shift	[ROOT, children]	[like, to, …]	A_1
LA$_{nsubj}$	[ROOT]	[like, to, …]	A_1 ∪ {nsubj(like, children)} = A_2
RA$_{root}$	[ROOT, like]	[to, play, …]	A_2 ∪{root(ROOT, like) = A_3
Shift	[ROOT, like, to]	[play, with, …]	A_3
LA$_{aux}$	[ROOT, like]	[play, with, …]	A_3∪{aux(play, to) = A_4
RA$_{xcomp}$	[ROOT, like, play]	[with their, …]	A_4∪{xcomp(like, play) = A_5

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Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A$, $w_i \neq$ ROOT
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$

Happy children like to play with their friends .

RA$_{xcomp}$	[ROOT, like, play]	[with their, …]	$A_4 \cup$ {xcomp(like, play) = A_5
RA$_{prep}$	[ROOT, like, play, with]	[their, friends, …]	$A_5 \cup$ {prep(play, with) = A_6
Shift	[ROOT, like, play, with, their]	[friends, .]	A_6
LA$_{poss}$	[ROOT, like, play, with]	[friends, .]	$A_6 \cup$ {poss(friends, their) = A_7
RA$_{pobj}$	[ROOT, like, play, with, friends]	[.]	$A_7 \cup$ {pobj(with, friends) = A_8
Reduce	[ROOT, like, play, with]	[.]	A_8
Reduce	[ROOT, like, play]	[.]	A_8
Reduce	[ROOT, like]	[.]	A_8
RA$_{punc}$	[ROOT, like, .]	[]	$A_8 \cup$ {punc(like, .) = A_9

You terminate as soon as the buffer is empty. Dependencies = A_9

Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A$, $w_i \neq$ ROOT
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$

[_ROOT_]$_S$ [Red figures on the screen indicated falling stocks]$_Q$

Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
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Shift

Example

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Left-arc

Example

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Right-arc

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Left-arc

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Right-arc

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Reduce

Example

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Reduce

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Left-arc

Example

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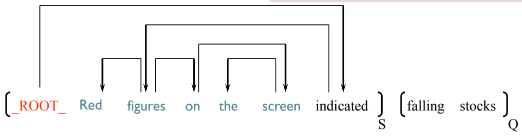

Right-arc

Example

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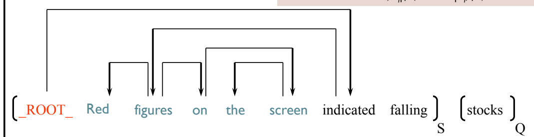
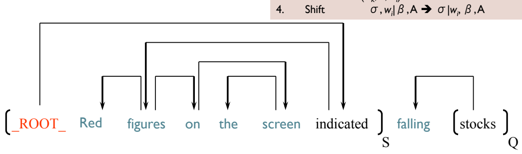


Shift

Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A, w_i \neq ROOT$
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$



Left-arc

Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A, w_i \neq ROOT$
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
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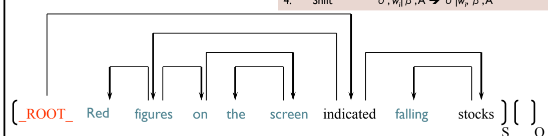
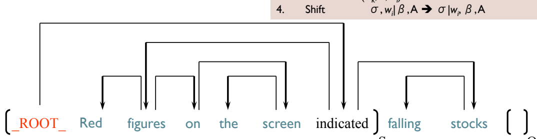


Right-arc

Example

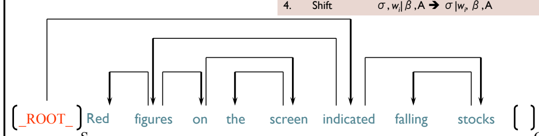
1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A, w_i \neq ROOT$
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$



Reduce

Example

1. Left-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma, w_j|\beta, A \cup \{r(w_j,w_i)\}$
   Precondition: $(w_k, r', w_i) \notin A, w_i \neq ROOT$
2. Right-Arc$_r$ $\sigma|w_i, w_j|\beta, A \rightarrow \sigma|w_i|w_j, \beta, A \cup \{r(w_i,w_j)\}$
3. Reduce $\sigma|w_i, \beta, A \rightarrow \sigma, \beta, A$
   Precondition: $(w_k, r', w_i) \in A$
4. Shift $\sigma, w_i|\beta, A \rightarrow \sigma|w_i, \beta, A$



Reduce

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MaltParser
[Nivre et al. 2008]

- We have left to explain how we choose the next action
- Each action is predicted by a discriminative classifier (often SVM, can be perceptron, maxent classifier) over each legal move
  - Max of 4 untyped choices, max of |R| × 2 + 2 when typed
  - Features: top of stack word, POS; first in buffer word, POS; etc.
- There is NO search (in the simplest and usual form)
  - But you could do some kind of beam search if you wish
- It provides VERY fast linear time parsing
- The model's accuracy is *slightly* below the best Lexicalized PCFGs (evaluated on dependencies), but
- It provides close to state of the art parsing performance

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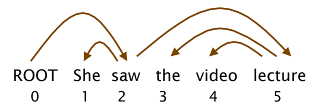
Evaluation of Dependency Parsing: (labeled) dependency accuracy



$$\text{Acc} = \frac{\text{\# correct deps}}{\text{\# of deps}}$$

UAS = 4 / 5 = 80%
LAS = 2 / 5 = 40%

Gold			
1	2	She	nsubj
2	0	saw	root
3	5	the	det
4	5	video	nn
5	2	lecture	dobj

Parsed			
1	2	She	nsubj
2	0	saw	root
3	4	the	det
4	5	video	nsubj
5	2	lecture	ccomp

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Representative performance numbers

- The CoNLL-X (2006) shared task provides evaluation numbers for various dependency parsing approaches over 13 languages
  - MALT: LAS scores from 65–92%, depending greatly on language/treebank
- Here we give a few UAS numbers for English to allow some comparison to constituency parsing

Parser	UAS%
Sagae and Lavie (2006) ensemble of dependency parsers	92.7
Charniak (2000) generative, constituency, as dependencies	92.2
Collins (1999) generative, constituency, as dependencies	91.7
McDonald and Pereira (2005) – MST graph-based dependency	91.5
Yamada and Matsumoto (2003) – transition-based dependency	90.4

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Projectivity

- Dependencies from a CFG tree using heads, must be projective
  - There must not be any crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words.
- But dependency theory normally does allow non-projective structures to account for displaced constituents
  - You can't easily get the semantics of certain constructions right without these nonprojective dependencies

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Handling non-projectivity

- The arc-eager algorithm we presented only builds projective dependency trees
- Possible directions to head:
  1. Just declare defeat on nonprojective arcs
  2. Use a dependency formalism which only admits projective representations (a CFG doesn't represent such structures…)
  3. Use a postprocessor to a projective dependency parsing algorithm to identify and resolve nonprojective links
  4. Add extra types of transitions that can model at least most non-projective structures
  5. Move to a parsing mechanism that does not use or require any constraints on projectivity (e.g., the graph-based MSTParser)

Dependencies encode relational structure

Relation Extraction with Stanford Dependencies

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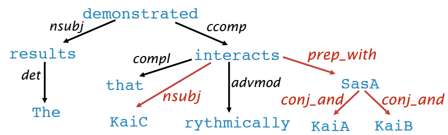
Dependency paths identify relations like protein interaction

[Erkan et al. EMNLP 07, Fundel et al. 2007]



KaiC ←nsubj interacts prep_with→ SasA
KaiC ←nsubj interacts prep_with→ SasA conj_and→ KaiA
KaiC ←nsubj interacts prep_with→ SasA conj_and→ KaiB

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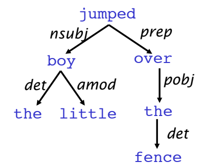
Stanford Dependencies

[de Marneffe et al. LREC 2006]

- The basic dependency representation is projective
- It can be generated by postprocessing headed phrase structure parses (Penn Treebank syntax)
- It can also be generated directly by dependency parsers, such as MaltParser, or the Easy-First Parser



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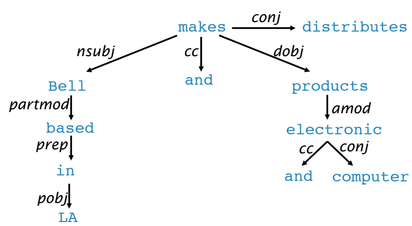
Graph modification to facilitate semantic analysis

Bell, based in LA, makes and distributes electronic and computer products.



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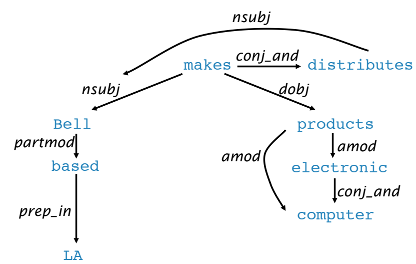

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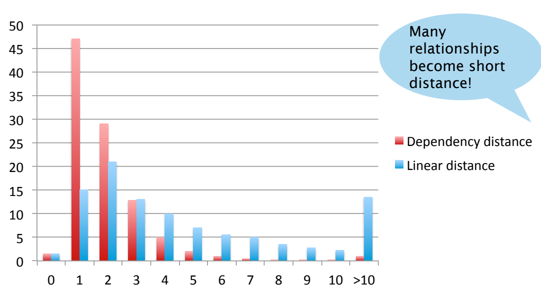
BioNLP 2009/2011 relation extraction shared tasks [Björne et al. 2009]



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