An efficient and linguistically rich statistical parser

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Linguistics & Statistics

- Linguistically rich parsers HPSG, LFG, &c.
  Non-local relations, function labels,
  morphological information.
  Often handwritten.
- Statistical Parsing
  Automatically induced from treebanks.
  Efficient
  Limited to constituents or projective dependencies.

This talk

1. Mild context-sensitivity
   Parsing with discontinuous constituents.
2. Data-Oriented Parsing
   Parsing with tree fragments.
3. Experiments

Two perspectives

Chomsky (1965):

Competence:
the idealized rules of language

Performance:
actual language use

Formal Grammar theory

Statistical NLP

This talk: Computational Linguistics should focus more on the latter.

Chomsky (1965). Aspects of the Theory of Syntax.

The Chomsky hierarchy

1. Unrestricted undecidable
2. Context-Sensitive PSPACE complete
3. Context-Free $O(n^3)$
4. Regular $O(n)$

Chomsky & Schützenberger (1959). The Algebraic Theory of Context-Free Languages.

Cross-Serial dependencies

Dutch:
dat Karel Marie Peter Hans laat helpen leren zwemmen

English:
that Charles lets Mary help Peter teach Hans to swim

NB: cross-serial easier to process than center embedding!
(Bach et al. 1986)

Bach et al. (1986). Crossed and nested dependencies in German and Dutch: A psycholinguistic study.

Joshi (1985)

Joshi (1985): How much context sensitivity is necessary (. . .)

Goal A grammar formalism that is efficiently parsable yet strong enough to describe natural language

Figure: Aravind K. Joshi

Mild Context-Sensitivity

Definition

Mild Context-Sensitivity

1. limited crossed dependencies
2. constant growth
3. polynomial time parsing

Tree-Adjoining Grammar:

Tree Substitution: combine tree fragments

Tree Adjunction: add adjuncts

Discontinuous Constituents

Example:

- Why did the chicken cross the road?
- The chicken crossed the road to get to the other side.

Non-local information in PTB: traces

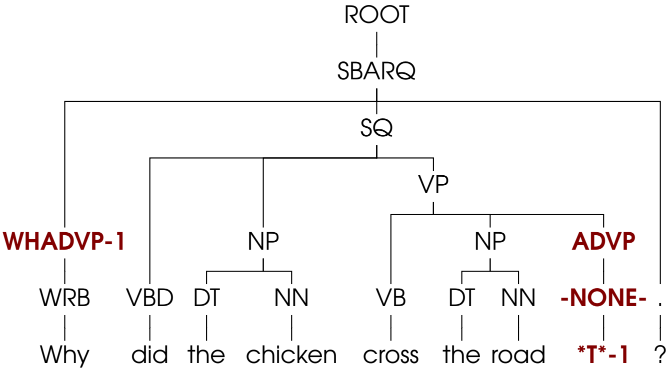


Figure: PTB-style annotation.

Discontinuous trees

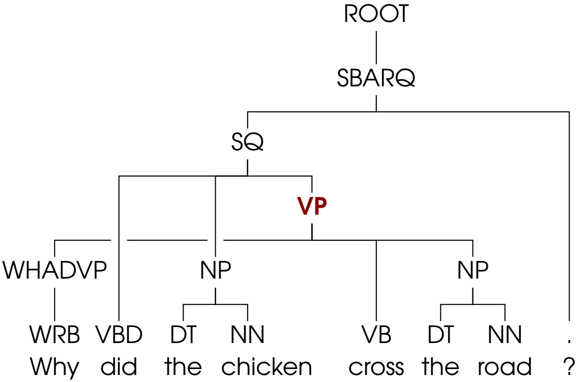


Figure: A tree with a discontinuous constituent.

Discontinuous constituents

Motivation:

- Handle flexible word-order, extraposition, &c.
- Capture argument structure
- Combine information from constituency & dependency structures

(NB: non-projectivity is a subset of discontinuous phenomena)

Discontinuous treebanks

Treebanks with discontinuous constituents:

German/Negra: Skut et al. (1997). An annotation scheme for free word order languages.

Dutch/Alpino: van der Beek (2002). The Alpino dependency treebank.

English/PTB (after conversion): Evang & Kallmeyer (2011). PLCFRS Parsing of English Discontinuous Constituents.

Swedish, Polish, . . .

Discontinuous trees

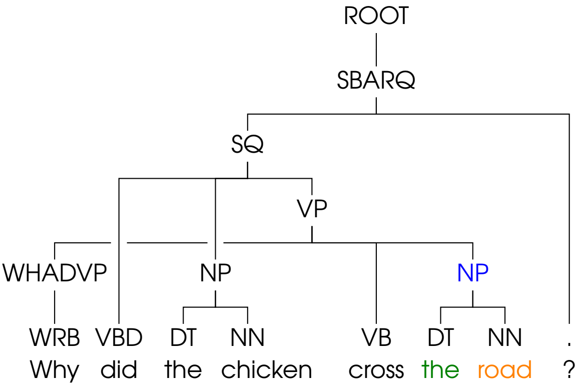


Figure: A tree with a discontinuous constituent.

Context-Free Grammar (CFG)

$$NP(ab) \rightarrow DT(a)\ NN(b)$$

Discontinuous trees

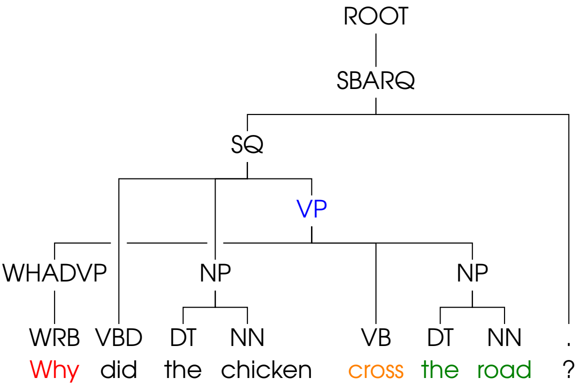


Figure: A tree with a discontinuous constituent.

Linear Context-Free Rewriting System (LCFRS)

$$VP_2(a, bc) \rightarrow WHADVP(a)\ VB(b)\ NP(c)$$

Discontinuous trees

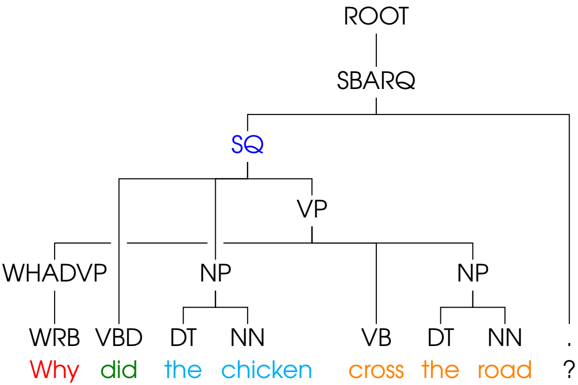


Figure: A tree with a discontinuous constituent.

Linear Context-Free Rewriting System (LCFRS)

$$VP_2(a, bc) \rightarrow WHADVP(a)\ VB(b)\ NP(c)$$
$$SQ(abcd) \rightarrow VBD(b)\ NP(c)\ VP_2(a, d)$$

Linear Context-Free Rewriting Systems

LCFRS are a generalization of CFG:
⇒ rewrite tuples, trees or graphs!

Vijay-Shanker et al. (1987): Structural descriptions (. . .) grammar formalisms.
Kallmeyer & Maier (2010, 2013). Data-driven parsing with probabilistic (LCFRS).

Linear Context-Free Rewriting Systems

LCFRS are a generalization of CFG:
⇒ rewrite tuples, trees or graphs!

linear: each variable on the left occurs once on the right & vice versa

context-free: apply productions based on what they rewrite

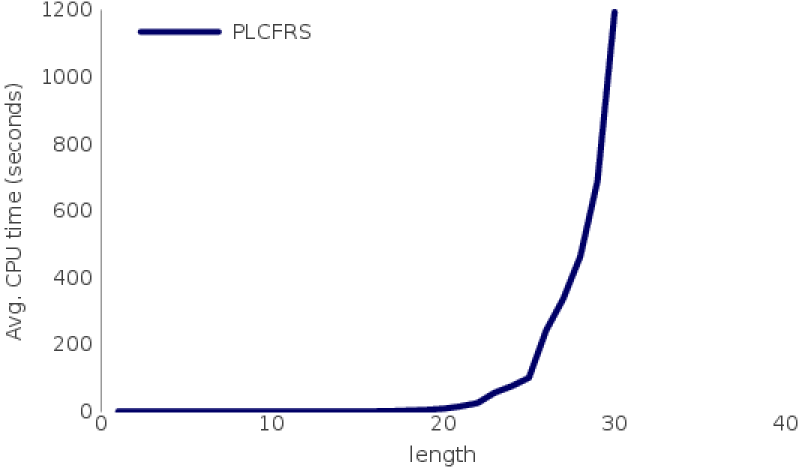
rewriting system: i.e., formal grammar

Parsing a binarized LCFRS has polynomial time complexity:

$$\mathcal{O}(n^{3\varphi})$$

Vijay-Shanker et al. (1987): Structural descriptions (. . .) grammar formalisms.
Kallmeyer & Maier (2010, 2013). Data-driven parsing with probabilistic (LCFRS).

But . . .



Negra dev. set, gold tags

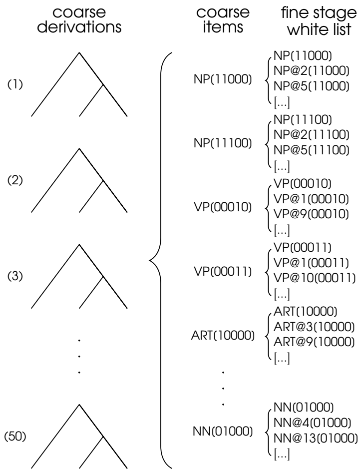
Pruning

Pruning can be based on:

1. Very little: e.g., beam threshold
2. Grammar: e.g., A* or context summary estimates
3. Sentence: e.g., coarse-to-fine parsing

Pauls & Klein (NAACL 2009), Hierarchical search for parsing.

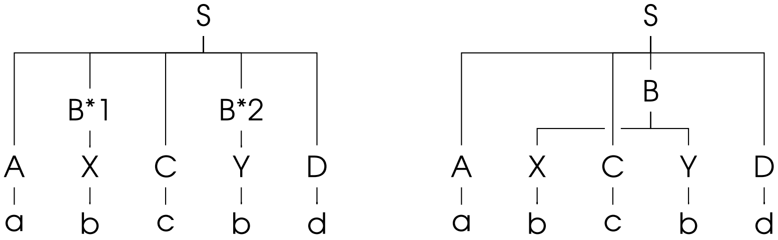
Coarse-to-fine



k-best PLCFRS derivations
help prune DOP derivations.

Charniak et al. (2006), Multi-level coarse-to-fine parsing

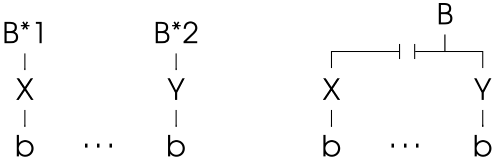
PCFG approximation of PLCFRS



- Transformation is reversible
- Increased independence assumption:
  ⇒ every component is a new node
- Language of PCFG is a superset of original PLCFRS
  ⇒ coarser, overgenerating PCFG ('split-PCFG')

Boyd (2007), Discontinuity revisited.

Coarse-to-fine from PCFG to PLCFRS

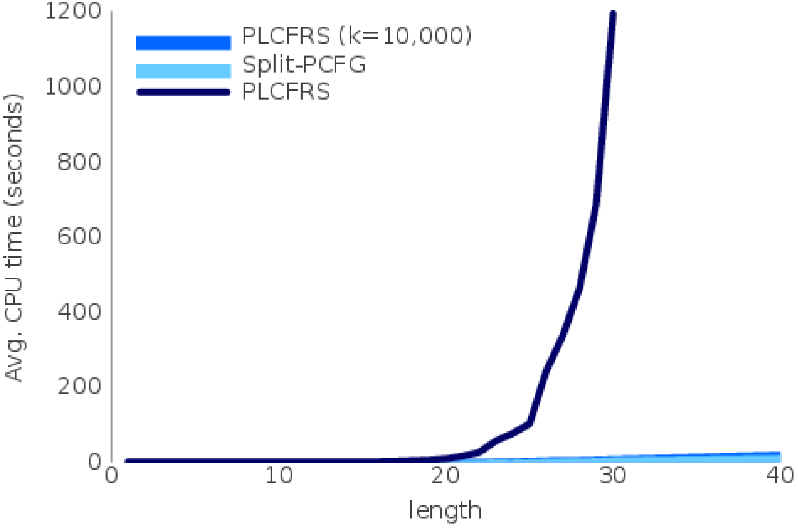


- For a discontinuous item, look up multiple items from PCFG chart (‘splitprune’)
- e.g.:

$$\left\{ \begin{matrix} NP{*}1 : [1, 2], \\ NP{*}2 : [4, 5] \end{matrix} \right\} \Rightarrow NP_2 : [1, 2;\ 4, 5]$$

Barthélemy et al. (2001) Guided parsing of range concatenation languages.
van Cranenburgh (2012), Efficient parsing with LCFRS

With coarse-to-fine



Negra dev. set, gold tags

Coarse-to-fine pipeline

Treebank grammars: G_0 Split-PCFG, G_1 PLCFRS

G_0 Split-PCFG

$\Downarrow$

G_1 PLCFRS

$\Downarrow$

G_2 *a large grammar*

Mildly context-sensitive: G_1 PLCFRS, G_2 *a large grammar*

prune parsing with G_{m+1} by only considering items in k-best G_m derivations.

Data-Oriented Parsing

Treebank grammar

trees ⇒ productions + rel. frequencies

⇒ problematic independence assumptions

Data-Oriented Parsing (DOP)

trees ⇒ fragments + rel. frequencies

fragments are arbitrarily sized chunks from the corpus

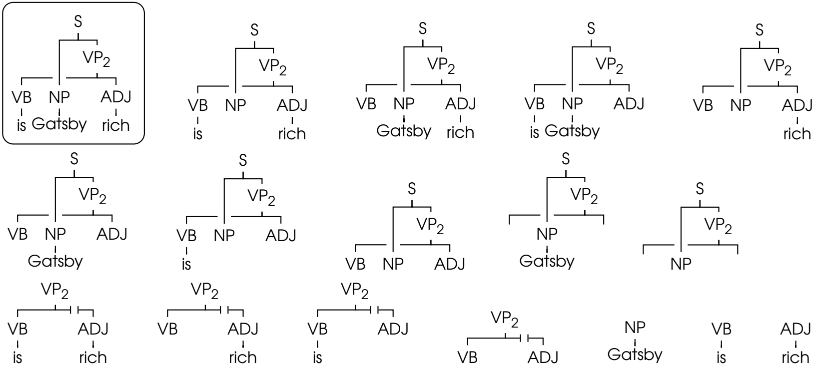
consider all possible fragments from treebank

…and "let the statistics decide"

Scha (1990): Lang. theory and lang. tech.; competence and performance

Bod (1992): A computational model of language performance

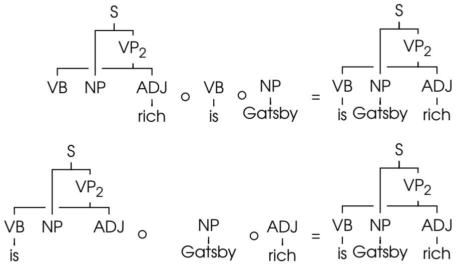
DOP fragments



$$P(f) = \frac{\text{count}(f)}{\sum_{f' \in F} \text{count}(f')} \text{ where } F = \{\, f' \mid root(f') = root(f) \,\}$$

Note: discontinuous frontier non-terminals mark destination of components

DOP derivation



$P(d) = 0.2$

$P(d) = 0.3$

Derivations for this tree $\qquad P(t) = 0.5$

$$P(d) = P(f_1 \circ \cdots \circ f_n) = \prod_{f \in d} p(f)$$

$$P(t) = P(d_1) + \cdots + P(d_n) = \sum_{d \in D(t)} \prod_{f \in d} p(f)$$

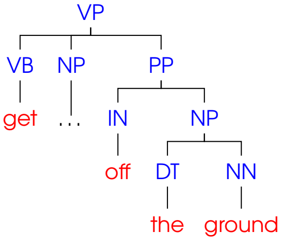
Tree-Substitution Grammar

This DOP model (Bod 1992) is based on Tree-Substitution Grammar (TSG):

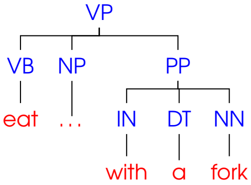
- Weakly equivalent to CFG; typically strongly equivalent as well; advantage is in stochastic power of Probabilistic TSG.
- Same Context-Free property as CFG, but multiple productions applied at once;
  $\Rightarrow$ captures more structural relations than PCFG.
- CFG backbone can be replaced with LCFRS to get Discontinuous Tree-Substitution Grammar ($\text{PTSG}_{\text{LCFRS}}$).

Tree Fragments

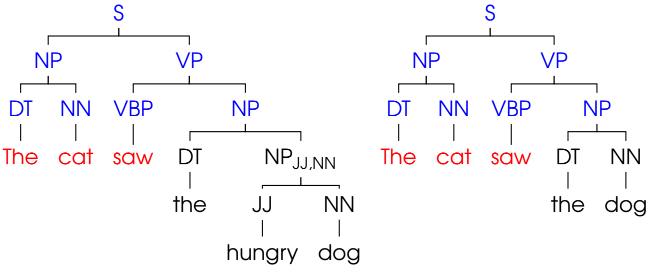
Multiword expressions (MWE):



Statistical regularities:



Double-DOP



Problem: Exponential number of fragments due to all-fragments assumption

- Extract fragments that occur at least twice in treebank
- For every pair of trees, extract maximal overlapping fragments
- Number of fragments is small enough to parse with directly

Sangati & Zuidema (2011). Accurate parsing w/compact TSGs: Double-DOP

Extract recurring fragments in linear average time

Tree kernel: find similarities in trees of treebank

- Worst case: need to compare every node to all other nodes in treebank
- Speed up comparisons by sorting nodes of trees:
  ⇒ Aligns potentially equal nodes, allowing us to skip the rest! (Moschitti 2006)
- Figure out fragments from list of matching nodes

Moschitti (2006): Making tree kernels practical for natural language learning
van Cranenburgh (2014), Extraction of (...) fragments w/linear average time

Extract recurring fragments in linear average time

Method, Corpus	Number of Trees	Number of Fragments	Time (hr:min) Wall	Time (hr:min) CPU
Sangati et al. (2010):				
QTK, WSJ 2–21	39,832	990,156	8:23	124:04
van Cranenburgh (2014):				
FTK*, WSJ 2–21	39,832	990,890	0:05	1:16
FTK, Gigaword, subset	502,424	9.7 million	9:54	$\sim$ 160

Wall clock time is when using 16 cores.

* Includes roaring bitmap datastructure (Chambi et al. 2014).

Sangati et al. (2010): Efficiently extract recurring tree fragments
van Cranenburgh (2014), Extraction of (. . .) fragments with a linear average

Experimental setup

English: Penn treebank, WSJ section
German: Tiger
Dutch: Lassy

Function labels

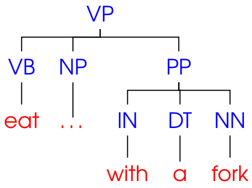
Syntactic categories (form): NP, VP, S, . . .

Function labels (function): SBJ, OBJ, TMP, LOC, . . .

- Classifier:
  - Blaheta & Charniak (2000), Assigning Function Tags to Parsed Text
- Integrate in grammar:
  - Gabbard et al. (2006), Fully parsing the Penn treebank
  - Fraser et al. (2013), Knowledge sources for constituent parsing of German

Evaluation: function tag accuracy over correctly parsed labeled bracketings.

State splits



- Tree fragments and state splits are (relatively) complementary:
  tree fragments include more context, but substitution is only restricted by the fine-grainedness of labels.
- Combine tree-substitution with manual state splits from:

  English: Klein & Manning (2003)
  German: Fraser et al. (2013)
  Dutch: new work

Preprocessing

- Binarize w/markovization (h=1, v=1)
- Simple unknown word model
  - Rare words replaced by features (model 4 from Stanford parser): `forty-two' ⇒ `_UNK-L-H-o`

Not reproduced: morphological tags, secondary parents

Can DOP handle discontinuity without LCFRS?

Negra dev set, gold tags:

Split-PCFG	Split-PCFG
$\Downarrow$	
PLCFRS	$\Downarrow$
$\Downarrow$	
PLCFRS Double-DOP	Split-Double-DOP
77.7 % F1	
41.5 % EX	

Can DOP handle discontinuity without LCFRS?

Negra dev set, gold tags:

Split-PCFG	Split-PCFG
$\Downarrow$	
PLCFRS	$\Downarrow$
$\Downarrow$	
PLCFRS Double-DOP	Split-Double-DOP
77.7 % F1	78.1 % F1
41.5 % EX	42.0 % EX

Answer: Yes!

Fragments can capture discontinuous contexts

Parsing results

Parser	F1	EX	func
GERMAN: Tiger			
Dep: HaNi2008	75.3	32.6	
2DOP: Cr et al	**78.2**	**40.0**	93.5
Dep: FeMa2015	82.6	45.9	
ENGLISH: WSJ			
PLCFRS: EvKa2011	79.0		
2DOP: Cr et al, WSJ	**87.0**	34.4	86.3
2DOP: SaZu2011, no disc.	87.9	33.7	
DUTCH: Lassy			
2DOP: Cr et al	76.6	34.0	92.8

HaNi: Hall & Nivre (2008); FeMa: Fernández-González & Martins (2015); SaZu: Sangati & Zuidema (2011); EvKa: Evang & Kallmeyer (2011); Cr et al: van Cranenburgh, Scha, Bod (submitted).

Recap

Linguistically rich: non-local relations, function tags
Efficiency: CFG base grammer, tree fragment extraction

Competence: idealized rules
Performance: actual language use

Tree fragments increase the abilities of a performance model w.r.t. discontinuous constituents, without increasing formal complexity.

THE END

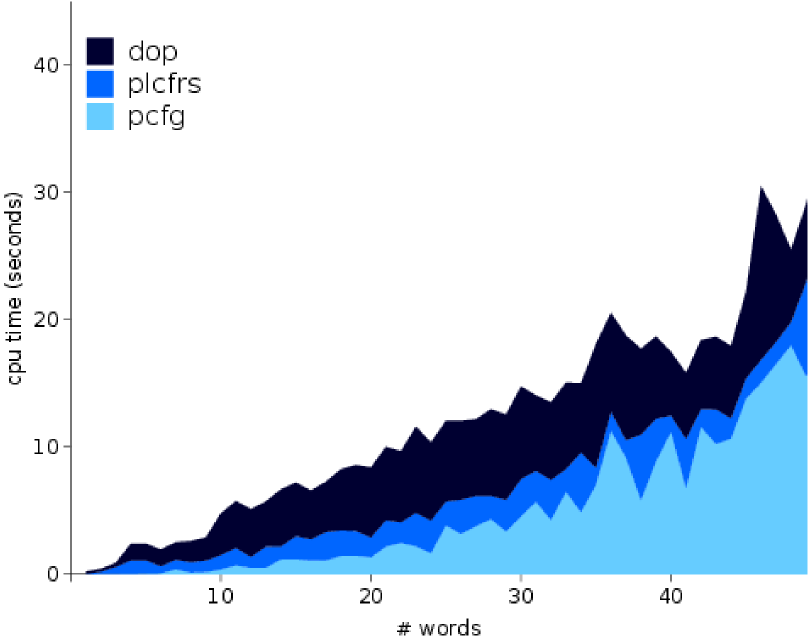
Codes: `http://github.com/andreasvc/disco-dop`

Papers: `http://andreasvc.github.io`

Wait ... there's more

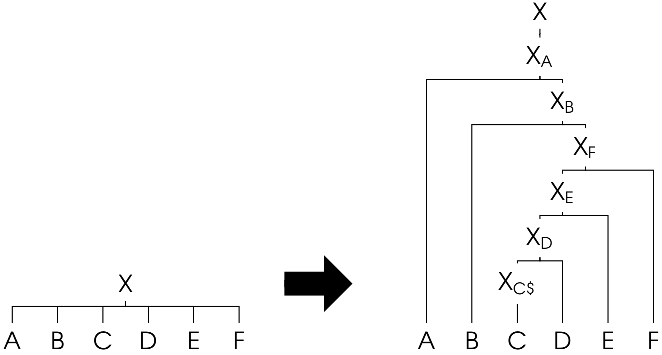
BACKUP SLIDES

Efficiency (Negra dev set)



Binarization

- mark heads of constituents
- head-outward binarization (parse head first)
- no parent annotation: $v = 1$
- horizontal Markovization: $h = 1$



Klein & Manning (2003): Accurate unlexicalized parsing.

Implementation details

- Cython: combines best of both worlds
  C speed, Python convenience.
- Where it matters, manual memory management & layout;
- e.g., grammar rules & edges compactly packed in arrays of `structs`.
- FWIW, lines of code:

Collins parser	C	3k	(!?)
bitpar	C++	6k	
disco-dop parser	Cython	21k	
Berkeley parser	Java	58k	
Charniak & Johnson parser	C++	62k	
Stanford parser	Java	151k	