Statistical NLP
Spring 2007

Lecture 17: Lexicalized Parsing

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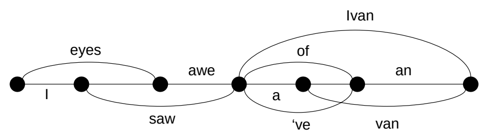
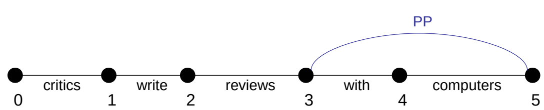
(Speech) Lattices

- There was nothing magical about words spanning exactly one position.
- When working with speech, we generally don't know how many words there are, or where they break.
- We can represent the possibilities as a lattice and parse these just as easily.



A Simple Chart Parser

- Chart parsers are sparse dynamic programs
- Ingredients:
  - Nodes: positions between words
  - Edges: spans of words with labels, represent the set of trees over those words rooted at x
  - A chart: records which edges we've built
  - An agenda: a holding pen for edges (a queue)
- We're going to figure out:
  - What edges can we build?
  - All the ways we built them.



Word Edges

- An edge found for the first time is called discovered. Edges go into the agenda on discovery.
- To initialize, we discover all word edges.

AGENDA

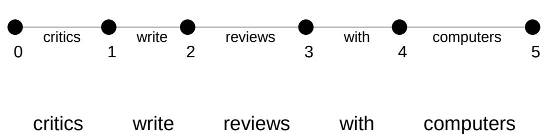
critics[0,1], write[1,2], reviews[2,3], with[3,4], computers[4,5]

CHART [EMPTY]

Unary Projection

- When we pop an word edge off the agenda, we check the lexicon to see what tag edges we can build from it

critics[0,1]	write[1,2]	reviews[2,3]	with[3,4]	computers[4,5]
NNS[0,1]	VBP[1,2]	NNS[2,3]	IN[3,4]	NNS[3,4]



The "Fundamental Rule"

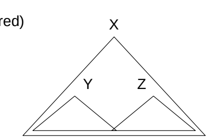
- When we pop edges off of the agenda:
  - Check for unary projections (NNS → critics, NP → NNS)

$$Y[i,j] \text{ with } X \rightarrow Y \text{ forms } X[i,j]$$

  - Combine with edges already in our chart (this is sometimes called the fundamental rule)

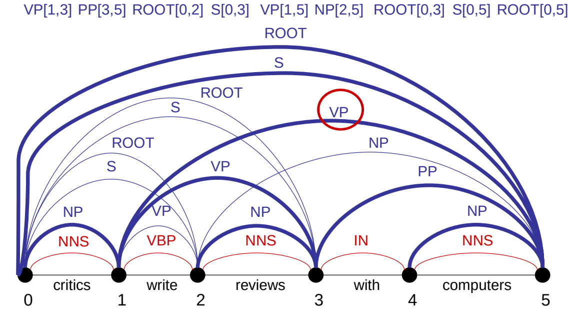
$$Y[i,j] \text{ and } Z[j,k] \text{ with } X \rightarrow Y\ Z \text{ form } X[i,k]$$

  - Enqueue resulting edges (if newly discovered)
  - Record backtraces (called traversals)
  - Stick the popped edge in the chart
- Queries a chart must support:
  - Is edge X:[i,j] in the chart?
  - What edges with label Y end at position j?
  - What edges with label Z start at position i?



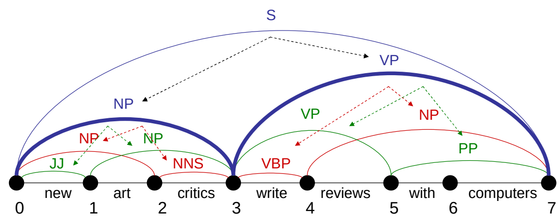
An Example

NNS[0,1] VBP[1,2] NNS[2,3] IN[3,4] NNS[3,4] NP[0,1] VP[1,2] NP[2,3] NP[4,5] S[0,2] VP[1,3] PP[3,5] ROOT[0,2] S[0,3] VP[1,5] NP[2,5] ROOT[0,3] S[0,5] ROOT[0,5]



Exploiting Substructure

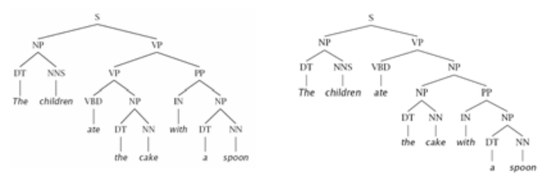
- Each edge records all the ways it was built (locally)
  - Can recursively extract trees
  - A chart may represent too many parses to enumerate (how many?)



Order Independence

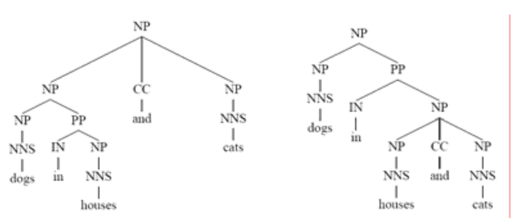
- A nice property:
  - It doesn't matter what policy we use to order the agenda (FIFO, LIFO, random).
  - Why? Invariant: before popping an edge:
    - Any edge X[i,j] that can be directly built from chart edges and a single grammar rule is either in the chart or in the agenda.
    - Convince yourselves this invariant holds!
  - This will not be true weighted parsers:
    - Instead must also insure that an edge has best score when added to the chart
    - Sufficient (but not necessary) to order agenda items by current best score

Problems with PCFGs?



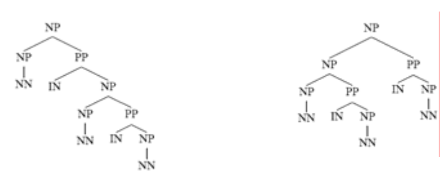
- If we do no annotation, these trees differ only in one rule:
  - VP → VP PP
  - NP → NP PP
- Parse will go one way or the other, regardless of words
- We addressed this in one way with unlexicalized grammars (how?)
- Lexicalization allows us to be sensitive to specific words

Problems with PCFGs



- What's different between basic PCFG scores here?
- What (lexical) correlations need to be scored?

Problems with PCFGs

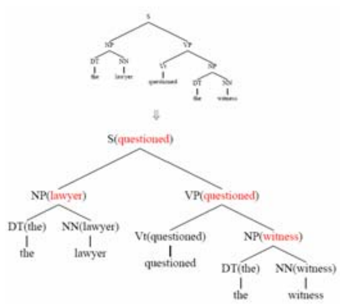


president of a company in Africa

- Another example of PCFG indifference
  - Left structure far more common
  - How to model this?
  - Really structural: "chicken with potatoes with gravy"
  - Lexical parsers model this effect, but not by virtue of being lexical

Lexicalized Trees

- Add "headwords" to each phrasal node
  - Syntactic vs. semantic heads
  - Headship not in (most) treebanks
  - Usually *use head rules*, e.g.:
    - NP:
      - Take leftmost NP
      - Take rightmost N*
      - Take rightmost JJ
      - Take right child
    - VP:
      - Take leftmost VB*
      - Take leftmost VP
      - Take left child



Lexicalized PCFGs?

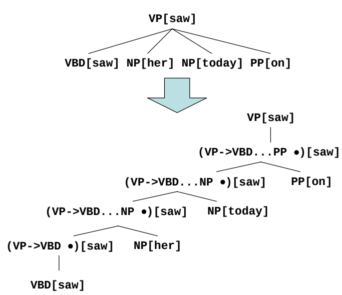
- Problem: we now have to estimate probabilities like

`VP(saw) -> VBD(saw) NP-C(her) NP(today)`

- Never going to get these atomically off of a treebank
- Solution: break up derivation into smaller steps

Lexical Derivation Steps

- Simple derivation of a local tree [simplified Charniak 97]



Still have to smooth with mono- and non-lexical backoffs

$$P(\mathtt{STOP}|\mathtt{VBD}[saw],\mathtt{VP},\mathtt{PP})$$

$$P(\mathtt{PP}[on]|\mathtt{VBD}[saw],\mathtt{VP},\mathtt{NP})$$

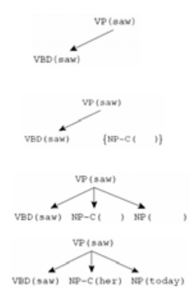
$$P(\mathtt{NP}[today]|\mathtt{VBD}[saw],\mathtt{VP},\mathtt{NP})$$

$$P(\mathtt{NP}[her]|\mathtt{VBD}[saw],\mathtt{VP},\mathtt{START})$$

$$P(\mathtt{VBD}[saw]|\mathtt{VP}[saw])$$

Lexical Derivation Steps

- Another derivation of a local tree [Collins 99]



Choose a head tag and word

Choose a complement bag

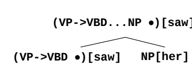
Generate children (incl. adjuncts)

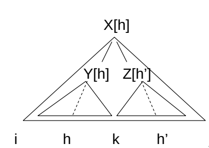
Recursively derive children

Naïve Lexicalized Parsing

- Can, in principle, use CKY on lexicalized PCFGs
  - $O(Rn^3)$ time and $O(Sn^2)$ memory
  - But $R = rV^2$ and $S = sV$
  - Result is completely impractical (why?)
  - Memory: 10K rules * 50K words * (40 words)^2 * 8 bytes ≈ 6TB
- Can modify CKY to exploit lexical sparsity
  - Lexicalized symbols are a base grammar symbol and a pointer into the input sentence, not any arbitrary word
  - Result: $O(rn^5)$ time, $O(sn^3)$
  - Memory: 10K rules * (40 words)^3 * 8 bytes ≈ 5GB

Lexicalized CKY

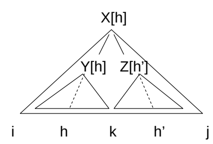


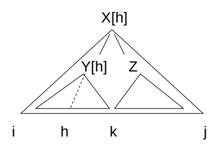



```
bestScore(X,i,j,h)
  if (j = i+1)
    return tagScore(X,s[i])
  else
    return
      max max       score(X[h]->Y[h] Z[h']) *
          k,X->YZ   bestScore(Y,i,k,h) *
                    bestScore(Z,k,j,h')
          max       score(X[h]->Y[h'] Z[h]) *
          k,X->YZ   bestScore(Y,i,k,h') *
                    bestScore(Z,k,j,h)
```

Quartic Parsing

- Turns out, you can do better [Eisner 99]

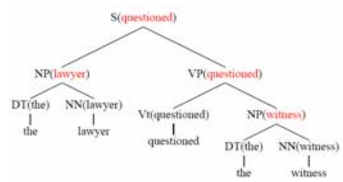


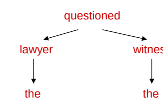


- Gives an $O(n^4)$ algorithm
- Still prohibitive in practice if not pruned

Dependency Parsing

- Lexicalized parsers can be seen as producing *dependency trees*

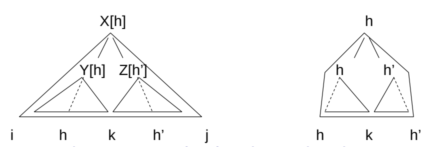




- Each local binary tree corresponds to an attachment in the dependency graph

Dependency Parsing

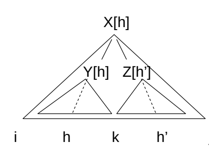
- Pure dependency parsing is only cubic [Eisner 99]



- Some work on *non-projective* dependencies
  - Common in, e.g. Czech parsing
  - Can do with MST algorithms [McDonald and Pereira 05]

Pruning with Beams

- The Collins parser prunes with per-cell beams [Collins 99]
  - Essentially, run the $O(n^5)$ CKY
  - Remember only a few hypotheses for each span <i,j>.
  - If we keep K hypotheses at each span, then we do at most $O(nK^2)$ work per span (why?)
  - Keeps things more or less cubic
- Also: certain spans are forbidden entirely on the basis of punctuation (crucial for speed)

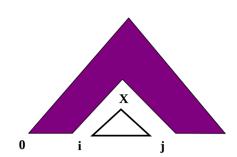


Pruning with a PCFG

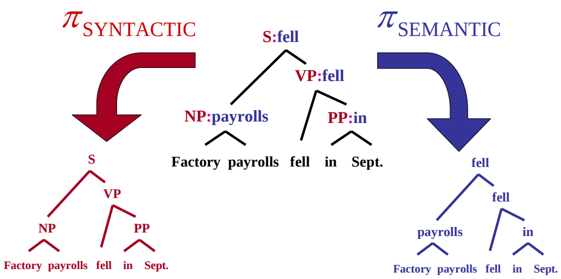
- The Charniak parser prunes using a two pass approach [Charniak 97+]
  - First, parse with the base grammar
  - For each X:[i,j] calculate P(X|i,j,s)
    - This isn't trivial, and there are clever speed ups
  - Second, do the full $O(n^5)$ CKY
    - Skip any X :[i,j] which had low (say, < 0.0001) posterior
  - Avoids almost all work in the second phase!
  - Currently the fastest lexicalized parser
- Charniak et al 06: can use more passes
- Petrov et al 07: can use many more passes

Pruning with A*

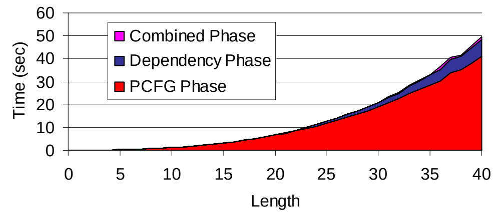
- You can also speed up the search without sacrificing optimality
- For agenda based parsers:
  - Can select which items to process first
  - Can do with any "figure of merit" [Charniak 98]
  - If your figure-of-merit is a valid A* heuristic, no loss of optimiality [Klein and Manning 03]



Projection-Based A*



A* Speedup



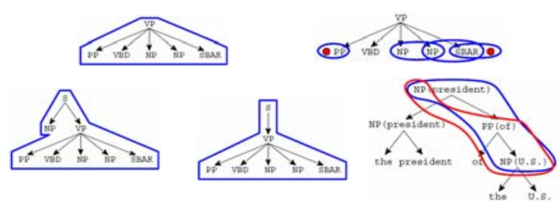
- Total time dominated by calculation of A* tables in each projection… $O(n^3)$

Results

- Some results
  - Collins 99 – 88.6 F1 (generative lexical)
  - Charniak and Johnson 05 – 89.7 / 91.3 F1 (generative lexical / reranked)
  - Petrov et al 06 – 90.7 F1 (generative unlexical)
  - McClosky et al 06 – 92.1 F1 (gen + rerank + self-train)
- However
  - Bilexical counts rarely make a difference (why?)
  - Gildea 01 – Removing bilexical counts costs < 0.5 F1
- Bilexical vs. monolexical vs. smart smoothing

Parse Reranking

- Assume the number of parses is very small
- We can represent each parse T as an arbitrary feature vector $\varphi(T)$
  - Typically, all local rules are features
  - Also non-local features, like how right-branching the overall tree is
  - [Charniak and Johnson 05] gives a rich set of features

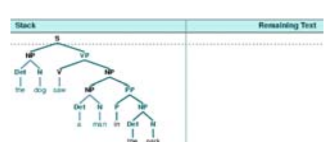


Parse Reranking

- Since the number of parses is no longer huge
  - Can enumerate all parses efficiently
  - Can use simple machine learning methods to score trees
  - E.g. maxent reranking: learn a binary classifier over trees where:
    - The top candidates are positive
    - All others are negative
    - Rank trees by P(+|T)
- The best parsing numbers are from reranking systems

Shift-Reduce Parsers

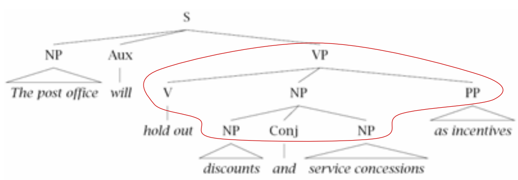
- Another way to derive a tree:



- Parsing
  - No useful dynamic programming search
  - Can still use beam search [Ratnaparkhi 97]

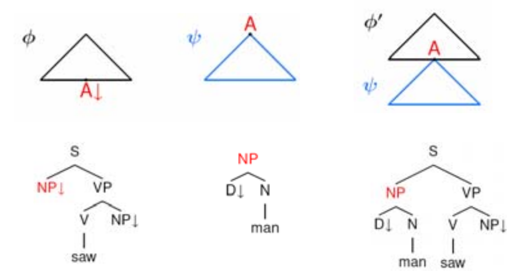
Data-oriented parsing:

- Rewrite large (possibly lexicalized) subtrees in a single step



- Formally, a *tree-insertion grammar*
- Derivational ambiguity whether subtrees were generated atomically or compositionally
- Most probable *parse* is NP-complete

TIG: Insertion



Derivational Representations

- Generative derivational models:

$$P(D) = \prod_{d_i \in D} P(d_i | d_0 \ldots d_{i-1})$$

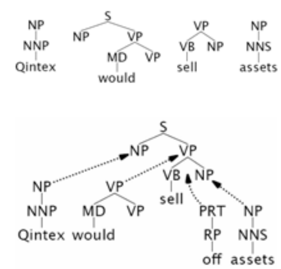
- How is a PCFG a generative derivational model?
- Distinction between *parses* and *parse derivations*.

$$P(T) = \sum_{D: D \to T} P(D)$$

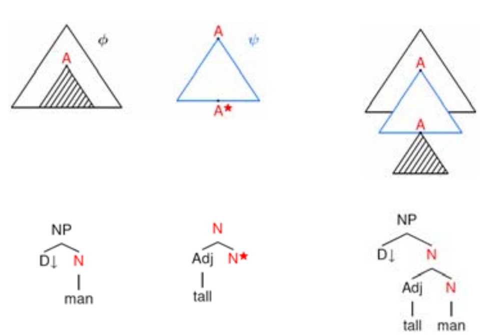
- How could there be multiple derivations?

Tree-adjoining grammars

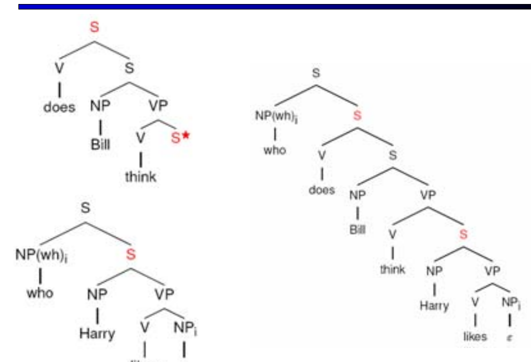
- Start with *local trees*
- Can insert structure with *adjunction* operators
- Mildly context-sensitive
- Models long-distance dependencies naturally
- … as well as other weird stuff that CFGs don't capture well (e.g. cross-serial dependencies)



TAG: Adjunction



TAG: Long Distance



CCG Parsing

- Combinatory Categorial Grammar
  - Fully (mono-) lexicalized grammar
  - Categories encode argument sequences
  - Very closely related to the lambda calculus (more later)
  - Can have spurious ambiguities (why?)

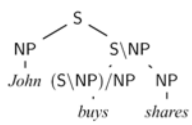
$\textit{John} \vdash \mathrm{NP}$

$\textit{shares} \vdash \mathrm{NP}$

$\textit{buys} \vdash (\mathrm{S}\backslash\mathrm{NP})/\mathrm{NP}$

$\textit{sleeps} \vdash \mathrm{S}\backslash\mathrm{NP}$

$\textit{well} \vdash (\mathrm{S}\backslash\mathrm{NP})\backslash(\mathrm{S}\backslash\mathrm{NP})$



Digression: Is NL a CFG?

- Cross-serial dependencies in Dutch