Natural Language Processing

Berkeley N L P

Parsing III

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Unsupervised Tagging

Unsupervised Tagging?

- AKA part-of-speech induction
- Task:
  - Raw sentences in
  - Tagged sentences out
- Obvious thing to do:
  - Start with a (mostly) uniform HMM
  - Run EM
  - Inspect results

EM for HMMs: Process

- Alternate between recomputing distributions over hidden variables (the tags) and reestimating parameters
- Crucial step: we want to tally up how many (fractional) counts of each kind of transition and emission we have under current params:

$$\text{count}(w, s) = \sum_{i: w_i = w} P(t_i = s | \mathbf{w})$$

$$\text{count}(s \to s') = \sum_i P(t_{i-1} = s, t_i = s' | \mathbf{w})$$

- Same quantities we needed to train a CRF!

Merialdo: Setup

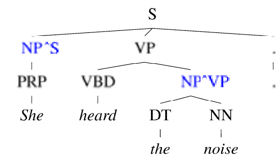
- Some (discouraging) experiments [Merialdo 94]
- Setup:
  - You know the set of allowable tags for each word
  - Fix k training examples to their true labels
    - Learn $P(w|t)$ on these examples
    - Learn $P(t|t_{-1},t_{-2})$ on these examples
  - On n examples, re-estimate with EM
- Note: we know allowed tags but not frequencies

Merialdo: Results

	Number of tagged sentences used for the initial model						
	0	100	2000	5000	10000	20000	all
Iter	Correct tags (% words) after ML on 1M words						
0	77.0	90.0	95.4	96.2	96.6	96.9	97.0
1	80.5	92.6	95.8	96.3	96.6	96.7	96.8
2	81.8	93.0	95.7	96.1	96.3	96.4	96.4
3	83.0	93.1	95.4	95.8	96.1	96.2	96.2
4	84.0	93.0	95.2	95.5	95.8	96.0	96.0
5	84.8	92.9	95.1	95.4	95.6	95.8	95.8
6	85.3	92.8	94.9	95.2	95.5	95.6	95.7
7	85.8	92.8	94.7	95.1	95.3	95.5	95.5
8	86.1	92.7	94.6	95.0	95.2	95.4	95.4
9	86.3	92.6	94.5	94.9	95.1	95.3	95.3
10	86.6	92.6	94.4	94.8	95.0	95.2	95.2

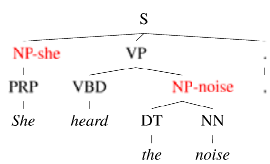
Latent Variable PCFGs

The Game of Designing a Grammar



- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Parent annotation [Johnson '98]

The Game of Designing a Grammar



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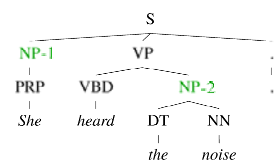
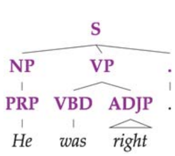
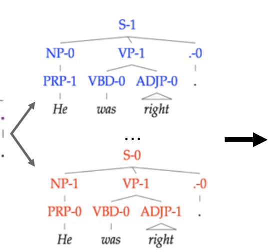


- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Parent annotation [Johnson '98]
  - Head lexicalization [Collins '99, Charniak '00]
  - Automatic clustering?

Latent Variable Grammars



Parse Tree T
Sentence w



Derivations $t : T$

Grammar G	
$S_0 \to NP_0\ VP_0$	?
$S_0 \to NP_1\ VP_0$	?
$S_0 \to NP_0\ VP_1$	?
$S_0 \to NP_1\ VP_1$	?
$S_1 \to NP_0\ VP_0$	?
...	
$S_1 \to NP_1\ VP_1$	?
...	
$NP_0 \to PRP_0$	?
$NP_0 \to PRP_1$	?
...	

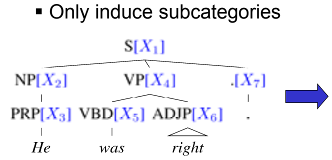
Lexicon	
$PRP_0 \to$ She	?
$PRP_1 \to$ She	?
...	
$VBD_0 \to$ was	?
$VBD_1 \to$ was	?
$VBD_2 \to$ was	?
...	

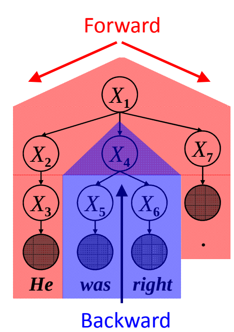
Parameters θ

Learning Latent Annotations

EM algorithm:

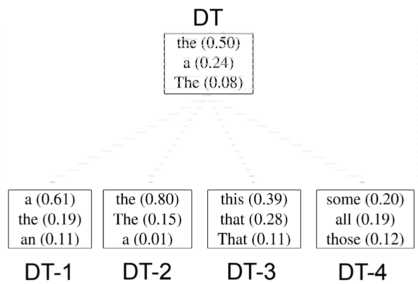
- Brackets are known
- Base categories are known
- Only induce subcategories



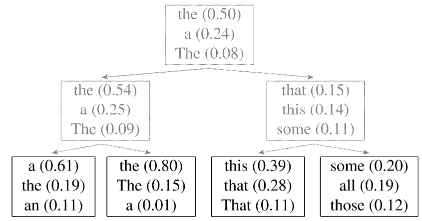


Just like Forward-Backward for HMMs.

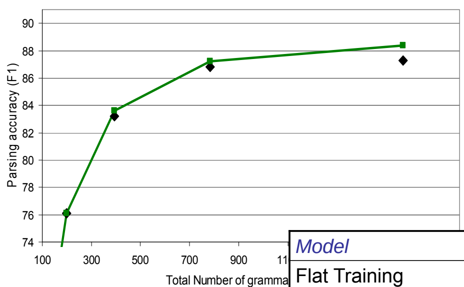
Refinement of the DT tag



Hierarchical refinement



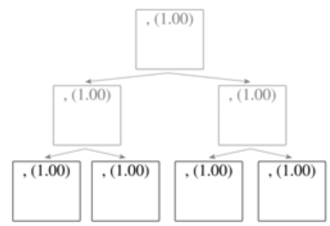
Hierarchical Estimation Results



Model	F1
Flat Training	87.3
Hierarchical Training	88.4

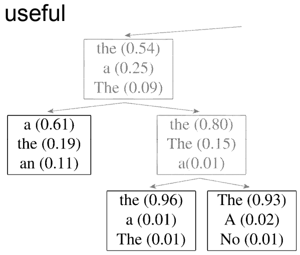
Refinement of the , tag

- Splitting all categories equally is wasteful:

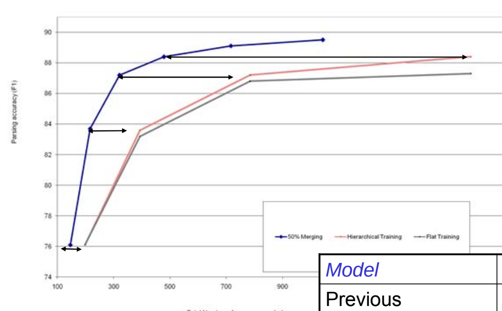


Adaptive Splitting

- Want to split complex categories more
- Idea: split everything, roll back splits which were least useful

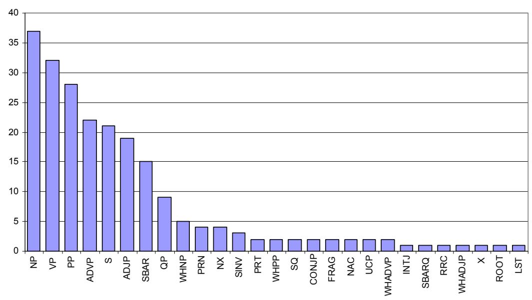


Adaptive Splitting Results

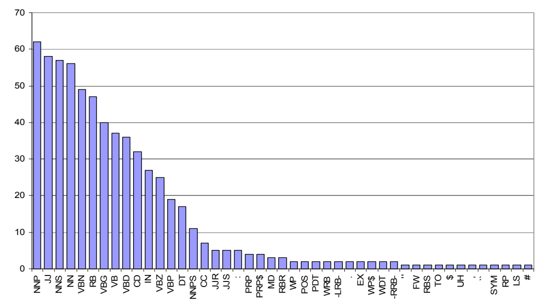


Model	F1
Previous	88.4
With 50% Merging	89.5

Number of Phrasal Subcategories



Number of Lexical Subcategories



Learned Splits

- Proper Nouns (NNP):

NNP-14	Oct.	Nov.	Sept.
NNP-12	John	Robert	James
NNP-2	J.	E.	L.
NNP-1	Bush	Noriega	Peters
NNP-15	New	San	Wall
NNP-3	York	Francisco	Street

- Personal pronouns (PRP):

PRP-0	It	He	I
PRP-1	it	he	they
PRP-2	it	them	him

Learned Splits

- Relative adverbs (RBR):

RBR-0	further	lower	higher
RBR-1	more	less	More
RBR-2	earlier	Earlier	later

- Cardinal Numbers (CD):

CD-7	one	two	Three
CD-4	1989	1990	1988
CD-11	million	billion	trillion
CD-0	1	50	100
CD-3	1	30	31
CD-9	78	58	34

Final Results (Accuracy)

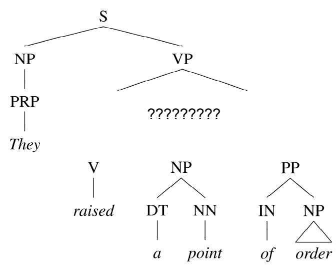
		≤ 40 words F1	all F1
ENG	Charniak&Johnson '05 (generative)	90.1	89.6
ENG	**Split / Merge**	**90.6**	**90.1**
GER	Dubey '05	76.3	-
GER	**Split / Merge**	**80.8**	**80.1**
CHN	Chiang et al. '02	80.0	76.6
CHN	**Split / Merge**	**86.3**	**83.4**

Still higher numbers from reranking / self-training methods

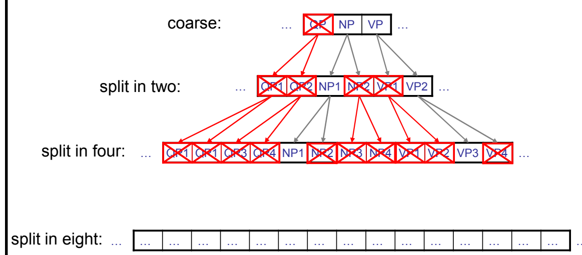
Efficient Parsing for Hierarchical Grammars

Coarse-to-Fine Inference

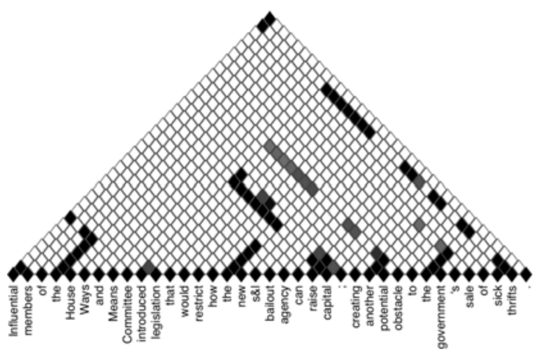
- Example: PP attachment



Hierarchical Pruning



Bracket Posteriors



1621 min

111 min

35 min

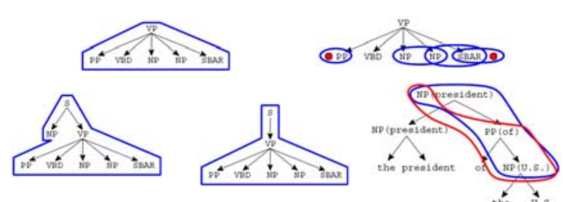
15 min

(no search error)

Other Syntactic Models

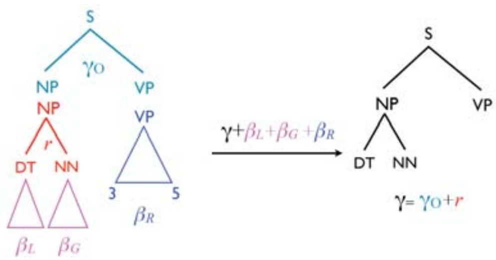
Parse Reranking

- 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



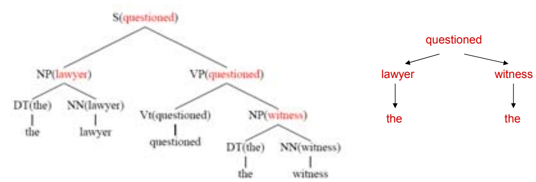
K-Best Parsing

[Huang and Chiang 05, Pauls, Klein, Quirk 10]



Dependency Parsing

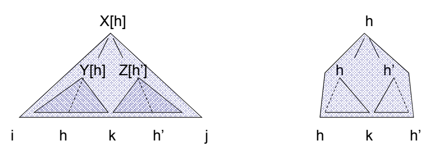
- Lexicalized parsers can be seen as producing *dependency trees*



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

Dependency Parsing

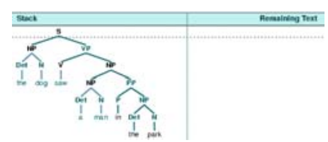
- Pure dependency parsing is only cubic [Eisner 99]



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

Shift-Reduce Parsers

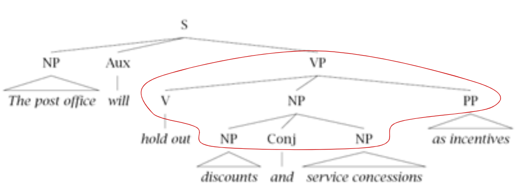
- Another way to derive a tree:



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

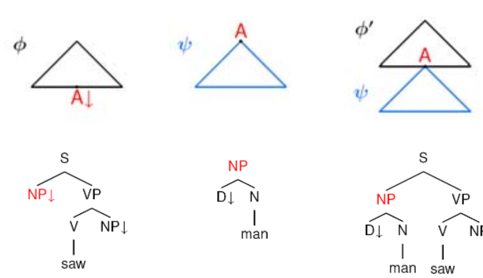
Data-oriented parsing:

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



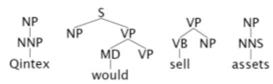
- Formally, a *tree-insertion grammar*
- Derivational ambiguity whether subtrees were generated atomically or compositionally
- Most probable *parse* is NP-complete

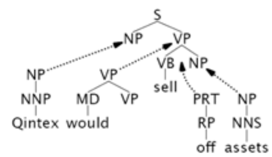
TIG: Insertion



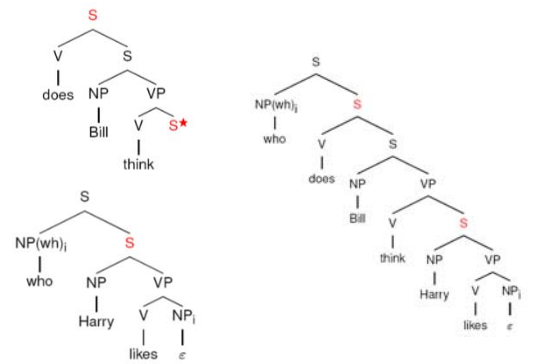
Tree-adjoining grammars

- 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: 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?)

$John \vdash \mathrm{NP}$

$shares \vdash \mathrm{NP}$

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

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

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