Statistical NLP
Spring 2007

Lecture 16: PCFGs

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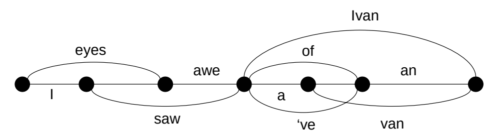
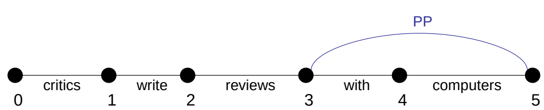
(Speech) Lattices

- 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

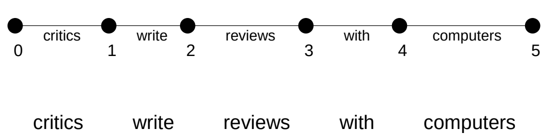
critics[0,1], write[1,2], reviews[2,3], with[3,4], computers[4,5]

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"

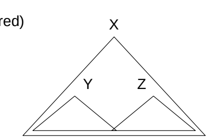
- When we pop edges off of the agenda:
  - Check for unary projections (NNS → critics, NP → NNS)

    Y[i,j] with X → Y forms X[i,j]

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

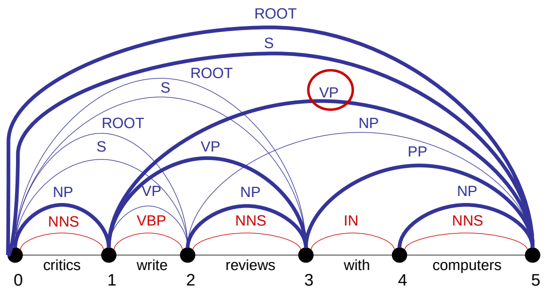
    Y[i,j] and Z[j,k] with X → Y Z form X[i,k]

  - 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?



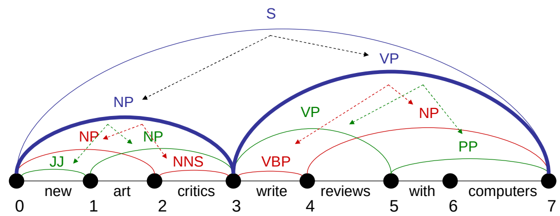
An Example

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 once we get weighted parsers.

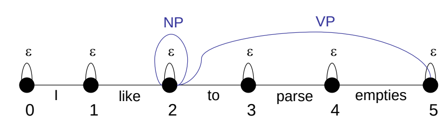
Empty Elements

- Sometimes we want to posit nodes in a parse tree that don't contain any pronounced words:

I want John to parse this sentence

I want [ ] to parse this sentence

- These are easy to add to our chart parser!
  - For each position i, add the "word" edge ε:[i,i]
  - Add rules like NP $\rightarrow$ ε to the grammar
  - That's it!

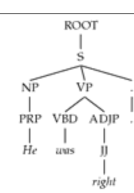


Treebank Sentences

```
( (S (NP-SBJ The move)
     (VP followed
         (NP (NP a round)
             (PP of
                 (NP (NP similar increases)
                     (PP by
                         (NP other lenders))
                     (PP against
                         (NP Arizona real estate loans)))))
         ,
         (S-ADV (NP-SBJ *)
                (VP reflecting
                    (NP (NP a continuing decline)
                        (PP-LOC in
                                (NP that market))))))
     .))
```

Treebank Parsing in 20 sec

- Need a PCFG for broad coverage parsing.
- Can take a grammar right off the trees (doesn't work well):



ROOT $\rightarrow$ S 1

S $\rightarrow$ NP VP . 1

NP $\rightarrow$ PRP 1

VP $\rightarrow$ VBD ADJP 1

.....

- Better results by enriching the grammar (e.g., lexicalization).
- Can also get reasonable parsers without lexicalization.

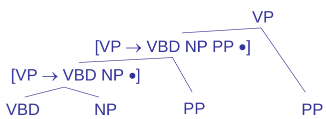
N-Ary Rules, Grammar States

- Often we want to write grammar rules like

  VP → VBD NP PP PP

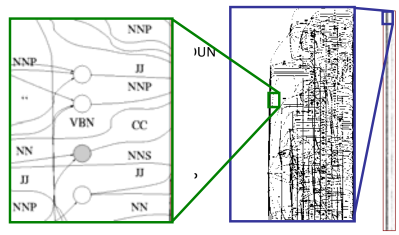
  which are not binary.

- We can work with these rules by introducing new intermediate symbols (states) into our grammar:



Treebank Grammar Scale

- Treebank grammars can be enormous!
  - As a set of FSTs, the raw grammar has ~10K states (why?).
  - Better parsers usually make the grammars larger, not smaller.

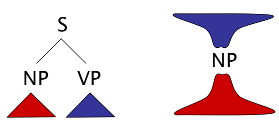


PCFGs and Independence

- Symbols in a PCFG define independence assumptions:

S → NP VP

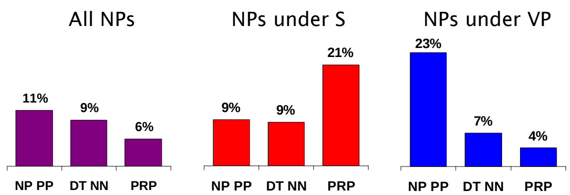
NP → DT NN



  - At any node, the material inside that node is independent of the material outside that node, given the label of that node.
  - Any information that statistically connects behavior inside and outside a node must flow through that node.

Non-Independence I

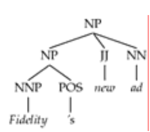
- Independence assumptions are often too strong.

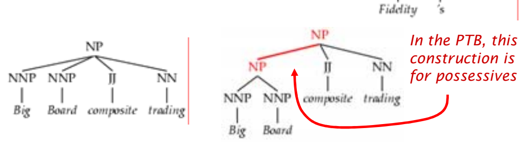


- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

Non-Independence II

- Who cares?
  - NB, HMMs, all make false assumptions!
  - For generation, consequences would be obvious.
  - For parsing, does it impact accuracy?
- Symptoms of overly strong assumptions:
  - Rewrites get used where they don't belong.
  - Rewrites get used too often or too rarely.

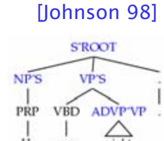




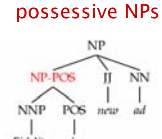
Breaking Up the Symbols

- We can relax independence assumptions by encoding dependencies into the PCFG symbols:

Parent annotation [Johnson 98]



Marking possessive NPs



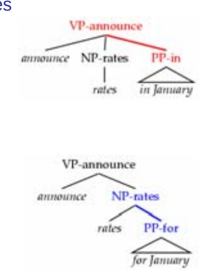
- What are the most useful "features" to encode?

Annotations

- Annotations split the grammar categories into sub-categories (in the original sense).
- Conditioning on history vs. annotating
  - P(NP^S → PRP) is a lot like P(NP → PRP | S)
  - P(NP-POS → NNP POS) isn't history conditioning.
- Feature / unification grammars vs. annotation
  - Can think of a symbol like NP^NP-POS as NP [parent:NP, +POS]
- After parsing with an annotated grammar, the annotations are then stripped for evaluation.

Lexicalization

- Lexical heads important for certain classes of ambiguities (e.g., PP attachment):
- Lexicalizing grammar creates a much larger grammar. (cf. next week)
  - Sophisticated smoothing needed
  - Smarter parsing algorithms
  - More data needed
- How necessary is lexicalization?
  - Bilexical vs. monolexical selection
  - Closed vs. open class lexicalization



Unlexicalized PCFGs

- What is meant by an "unlexicalized" PCFG?
  - Grammar not systematically specified to the level of lexical items
    - NP [stocks] is not allowed
    - NP^S-CC is fine
  - Closed vs. open class words (NP^S [the])
    - Long tradition in linguistics of using function words as features or markers for selection
    - Contrary to the bilexical idea of semantic heads
    - Open-class selection really a proxy for semantics
- It's kind of a gradual transition from unlexicalized to lexicalized (but heavily smoothed) grammars.

Typical Experimental Setup

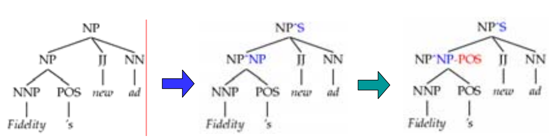
- Corpus: Penn Treebank, WSJ

Training:	sections	02-21
Development:	section	22 (here, first 20 files)
Test:	section	23

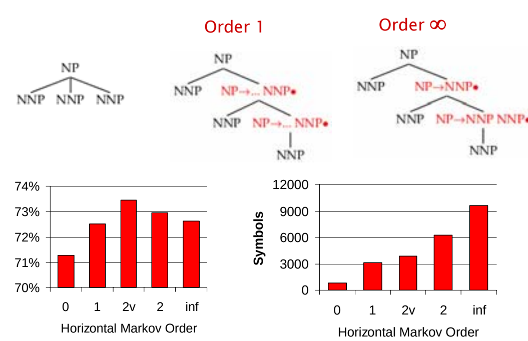
- Accuracy – F1: harmonic mean of per-node labeled precision and recall.
- Here: also size – number of symbols in grammar.
  - Passive / complete symbols: NP, NP^S
  - Active / incomplete symbols: NP → NP CC •

Multiple Annotations

- Each annotation done in succession
  - Order does matter
  - Too much annotation and we'll have sparsity issues

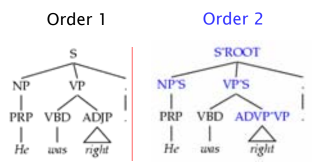


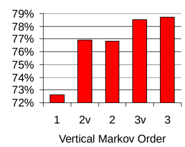
Horizontal Markovization

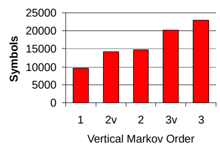


Vertical Markovization

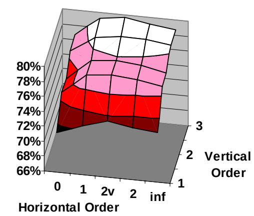
- Vertical Markov order: rewrites depend on past *k* ancestor nodes.
  (cf. parent annotation)

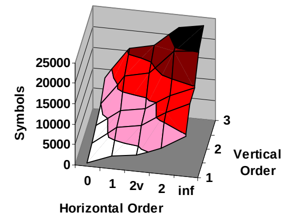






Vertical and Horizontal



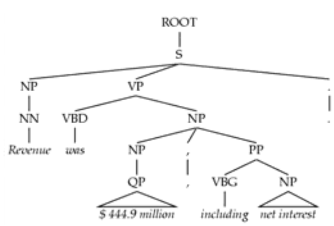


- Examples:
  - Raw treebank: v=1, h=∞
  - Johnson 98: v=2, h=∞
  - Collins 99: v=2, h=2
  - Best F1: v=3, h=2v

Model	F1	Size
Base: v=h=2v	77.8	7.5K

Unary Splits

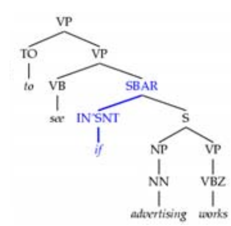
- Problem: unary rewrites used to transmute categories so a high-probability rule can be used.
- Solution: Mark unary rewrite sites with -U



Annotation	F1	Size
Base	77.8	7.5K
UNARY	78.3	8.0K

Tag Splits

- Problem: Treebank tags are too coarse.
- Example: Sentential, PP, and other prepositions are all marked IN.
- Partial Solution:
  - Subdivide the IN tag.



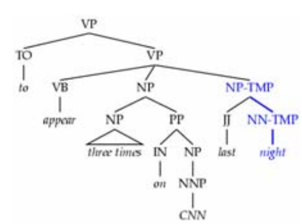
Annotation	F1	Size
Previous	78.3	8.0K
SPLIT-IN	80.3	8.1K

Other Tag Splits

	F1	Size
UNARY-DT: mark demonstratives as DT^U ("the X" vs. "those")	80.4	8.1K
UNARY-RB: mark phrasal adverbs as RB^U ("quickly" vs. "very")	80.5	8.1K
TAG-PA: mark tags with non-canonical parents ("not" is an RB^VP)	81.2	8.5K
SPLIT-AUX: mark auxiliary verbs with –AUX [cf. Charniak 97]	81.6	9.0K
SPLIT-CC: separate "but" and "&" from other conjunctions	81.7	9.1K
SPLIT-%: "%" gets its own tag.	81.8	9.3K

Treebank Splits

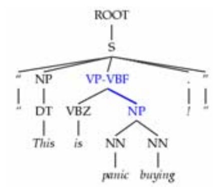
- The treebank comes with some annotations (e.g., -LOC, -SUBJ, etc).
  - Whole set together hurt the baseline.
  - One in particular is very useful (NP-TMP) when pushed down to the head tag (why?).
  - Can mark gapped S nodes as well.



Annotation	F1	Size
Previous	81.8	9.3K
NP-TMP	82.2	9.6K
GAPPED-S	82.3	9.7K

Yield Splits

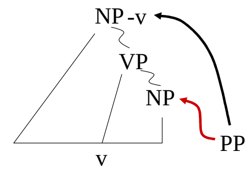
- Problem: sometimes the behavior of a category depends on something inside its future yield.
- Examples:
  - Possessive NPs
  - Finite vs. infinite VPs
  - Lexical heads!
- Solution: annotate future elements into nodes.
  - Lexicalized grammars do this (in very careful ways – why?).



Annotation	F1	Size
Previous	82.3	9.7K
POSS-NP	83.1	9.8K
SPLIT-VP	85.7	10.5K

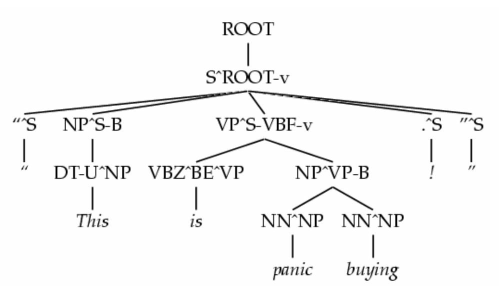
Distance / Recursion Splits

- Problem: vanilla PCFGs cannot distinguish attachment heights.
- Solution: mark a property of higher or lower sites:
  - Contains a verb.
  - Is (non)-recursive.
    - Base NPs [cf. Collins 99]
    - Right-recursive NPs



Annotation	F1	Size
Previous	85.7	10.5K
BASE-NP	86.0	11.7K
DOMINATES-V	86.9	14.1K
RIGHT-REC-NP	87.0	15.2K

A Fully Annotated (Unlex) Tree

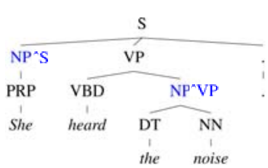


Some Test Set Results

Parser	LP	LR	F1	CB	0 CB
Magerman 95	84.9	84.6	**84.7**	1.26	56.6
Collins 96	86.3	85.8	**86.0**	1.14	59.9
Unlexicalized	86.9	85.7	**86.3**	1.10	60.3
Charniak 97	87.4	87.5	**87.4**	1.00	62.1
Collins 99	88.7	88.6	**88.6**	0.90	67.1

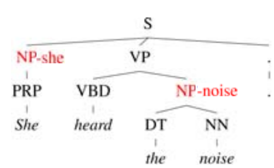
- Beats "first generation" lexicalized parsers.
- Lots of room to improve – more complex models next.

The Game of Designing a Grammar



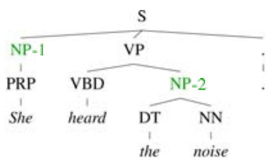
- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Parent annotation [Johnson '98]

The Game of Designing a Grammar



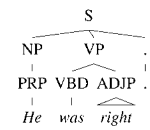
- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Parent annotation [Johnson '98]
  - Head lexicalization [Collins '99, Charniak '00]

The Game of Designing a Grammar



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

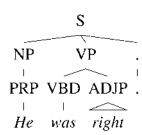
Manual Annotation



- Manually split categories
  - NP: subject vs object
  - DT: determiners vs demonstratives
  - IN: sentential vs prepositional
- Advantages:
  - Fairly compact grammar
  - Linguistic motivations
- Disadvantages:
  - Performance leveled out
  - Manually annotated

Model	*F1*
Naïve Treebank Grammar	72.6
Klein & Manning '03	86.3

Automatic Annotation Induction

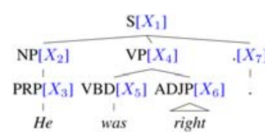


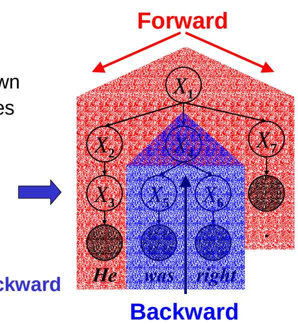
- Advantages:
  - Automatically learned:
    Label *all* nodes with latent variables.
    Same number k of subcategories for all categories.
- Disadvantages:
  - Grammar gets too large
  - Most categories are oversplit while others are undersplit.

Model	*F1*
Klein & Manning '03	86.3
Matsuzaki et al. '05	86.7

Learning Latent Annotations

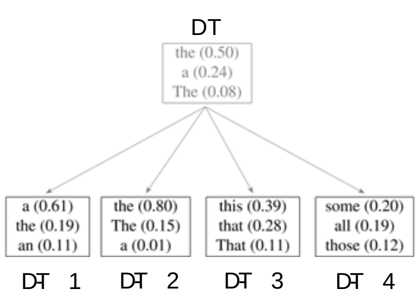
EM algorithm:
- Brackets are known
- Base categories are known
- Only induce subcategories



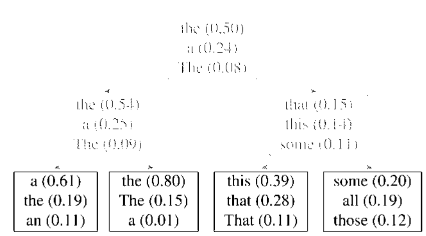


Just like Forward-Backward for HMMs.

Refinement of the DT tag

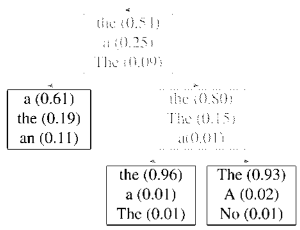


Hierarchical refinement



Adaptive Splitting

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

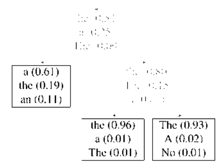


Adaptive Splitting

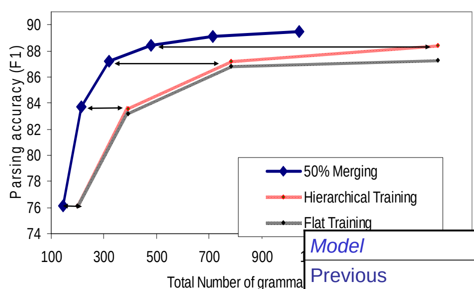
- Evaluate loss in likelihood from removing each split =

$$\frac{\textit{Data likelihood with split reversed}}{\textit{Data likelihood with split}}$$

- No loss in accuracy when 50% of the splits are reversed.

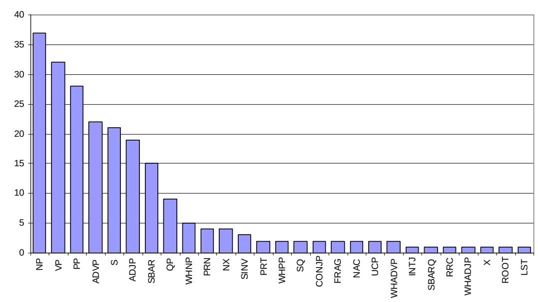


Adaptive Splitting Results

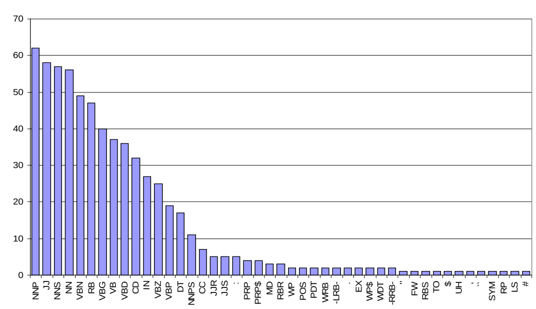


Model	*F1*
Previous	88.4
With 50% Merging	89.5

Number of Phrasal Subcategories



Number of Lexical Subcategories



Final Results

Parser	*F1* ≤ *40 words*	*F1* *all words*
Klein & Manning '03	86.3	85.7
Matsuzaki et al. '05	86.7	86.1
Collins '99	88.6	88.2
Charniak & Johnson '05	90.1	89.6
Petrov et. al. 06	90.2	89.7

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