Statistical NLP

Spring 2009

Lecture 13: Parsing I

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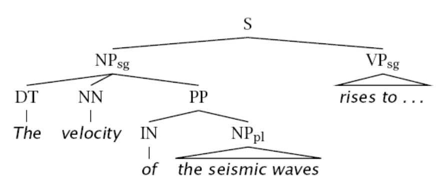
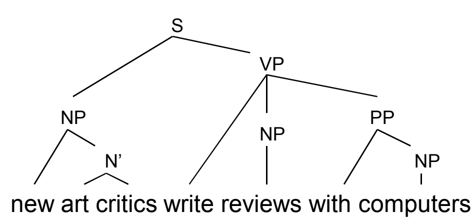
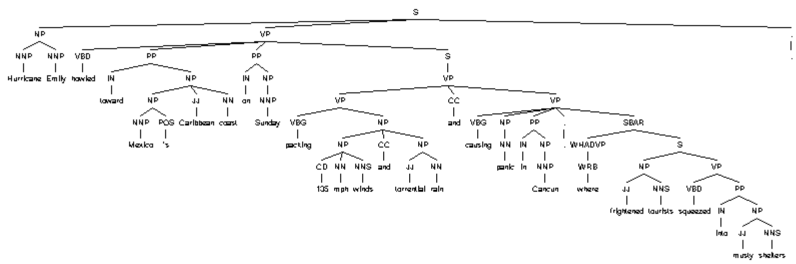
Phrase Structure Parsing

- Phrase structure parsing organizes syntax into *constituents* or *brackets*
- In general, this involves nested trees
- Linguists can, and do, argue about details
- Lots of ambiguity
- Not the only kind of syntax…





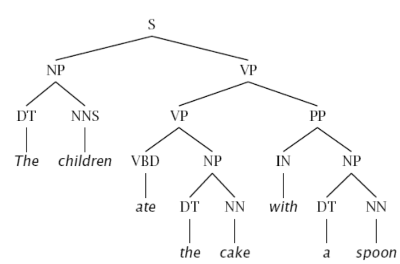
Example Parse



Hurricane Emily howled toward Mexico 's Caribbean coast on Sunday packing 135 mph winds and torrential rain and causing panic in Cancun , where frightened tourists squeezed into musty shelters .

Constituency Tests

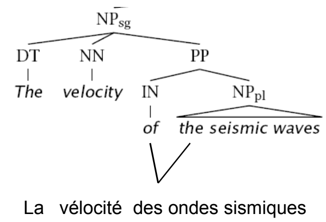
- How do we know what nodes go in the tree?
- Classic constituency tests:
  - Substitution by *proform*
  - Question answers
  - Semantic gounds
    - Coherence
    - Reference
    - Idioms
  - Dislocation
  - Conjunction



- Cross-linguistic arguments, too

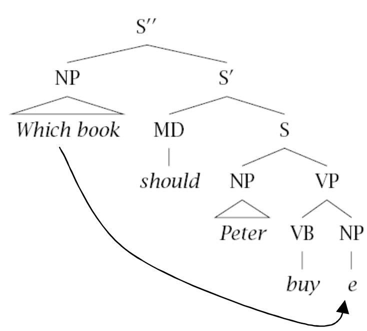
Conflicting Tests

- Constituency isn't always clear
  - Units of transfer:
    - think about ~ penser à
    - talk about ~ hablar de
  - Phonological reduction:
    - I will go → I'll go
    - I want to go → I wanna go
    - a le centre → au centre
  - Coordination
    - He went to and came from the store.



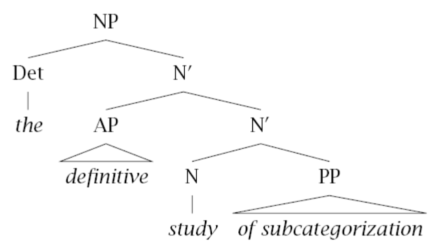
Non-Local Phenomena

- Dislocation / gapping
    - Why did the postman think that the neighbors were home?
    - A debate arose which continued until the election.
- Binding
  - Reference
    - The IRS audits itself
  - Control
    - I want to go
    - I want you to go

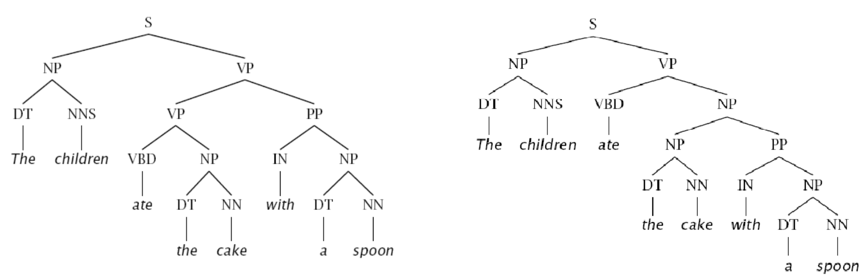


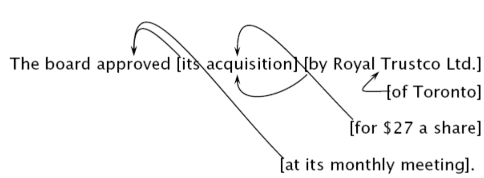
Regularity of Rules

- Argumentation
- Adjunction
- Coordination
- X' Theory



PP Attachment





PP Attachment

V	N1	P	N2	Attachment
join	board	as	director	V
is	chairman	of	N.V.	N
using	crocidolite	in	filters	V
bring	attention	to	problem	V
is	asbestos	in	products	N
making	paper	for	filters	N
including	three	with	cancer	N

Method	Accuracy
Always noun attachment	59.0
Most likely for each preposition	72.2
Average Human (4 head words only)	88.2
Average Human (whole sentence)	93.2

Attachments

- I cleaned the dishes from dinner
- I cleaned the dishes with detergent
- I cleaned the dishes in my pajamas
- I cleaned the dishes in the sink

Syntactic Ambiguities I

- Prepositional phrases:
  They cooked the beans in the pot on the stove with handles.
- Particle vs. preposition:
  The puppy tore up the staircase.
- Complement structures
  The tourists objected to the guide that they couldn't hear.
  She knows you like the back of her hand.
- Gerund vs. participial adjective
  Visiting relatives can be boring.
  Changing schedules frequently confused passengers.

Syntactic Ambiguities II

- Modifier scope within NPs
  impractical design requirements
  plastic cup holder
- Multiple gap constructions
  The chicken is ready to eat.
  The contractors are rich enough to sue.
- Coordination scope:
  Small rats and mice can squeeze into holes or cracks in the wall.

Human Processing

- Garden pathing:

  the man who hunts ducks out on weekends

  the cotton shirts are made from grows in Mississippi

  the daughter of the king's son loves himself

- Ambiguity maintenance

  Have the police . . . eaten their supper?
  come in and look around.
  taken out and shot.

Classical NLP: Parsing

- Write symbolic or logical rules:

Grammar (CFG)		Lexicon
ROOT → S	NP → NP PP	NN → interest
S → NP VP	VP → VBP NP	NNS → raises
NP → DT NN	VP → VBP NP PP	VBP → interest
NP → NN NNS	PP → IN NP	VBZ → raises
		…

- Use deduction systems to prove parses from words
  - Minimal grammar on "Fed raises" sentence: 36 parses
  - Simple 10-rule grammar: 592 parses
  - Real-size grammar: many millions of parses
- This scaled very badly, didn't yield broad-coverage tools

Probabilistic Context-Free Grammars

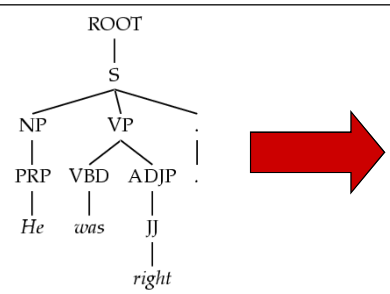
- A context-free grammar is a tuple <*N, T, S, R*>
  - *N* : the set of non-terminals
    - Phrasal categories: S, NP, VP, ADJP, etc.
    - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
  - *T* : the set of terminals (the words)
  - *S* : the start symbol
    - Often written as ROOT or TOP
    - *Not* usually the sentence non-terminal S
  - *R* : the set of rules
    - Of the form $X \rightarrow Y_1 Y_2 \ldots Y_k$, with $X, Y_i \in N$
    - Examples: $S \rightarrow NP\ VP$, $VP \rightarrow VP\ CC\ VP$
    - Also called rewrites, productions, or local trees
- A PCFG adds:
  - A top-down production probability per rule $P(Y_1 Y_2 \ldots Y_k \mid X)$

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 Grammars

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

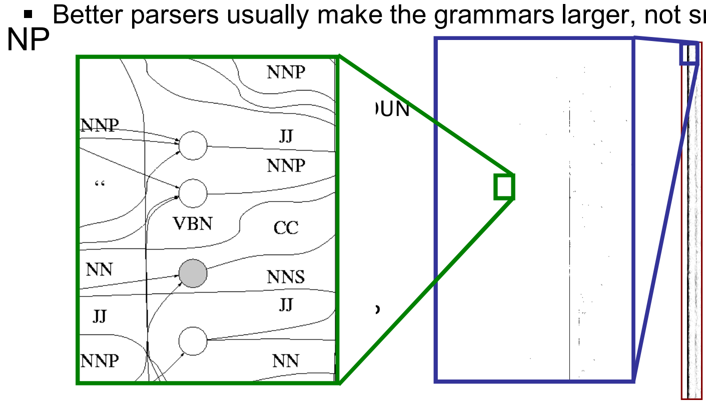


ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1
…..	

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

Treebank Grammar Scale

- Treebank grammars can be enormous
  - As FSAs, the raw grammar has ~10K states, excluding the lexicon
  - Better parsers usually make the grammars larger, not smaller

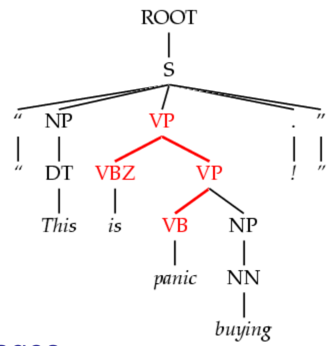


Dark Ambiguities

- *Dark ambiguities*: most analyses are shockingly bad (meaning, they don't have an interpretation you can get your mind around)

This analysis corresponds to the correct parse of

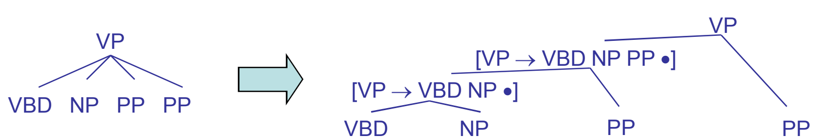
"This will panic buyers ! "



- Unknown words and new usages
- Solution: We need mechanisms to focus attention on the best ones, probabilistic techniques do this

Chomsky Normal Form

- Chomsky normal form:
  - All rules of the form X → Y Z or X → w
  - In principle, this is no limitation on the space of (P)CFGs
    - N-ary rules introduce new non-terminals



    - Unaries / empties are "promoted"
  - In practice it's kind of a pain:
    - Reconstructing n-aries is easy
    - Reconstructing unaries is trickier
    - The straightforward transformations don't preserve tree scores
  - Makes parsing algorithms simpler!

A Recursive Parser

- Here's a recursive (CNF) parser:

```
bestParse(X,i,j,s)
   if (j = i+1)
       return X -> s[i]
   (X->YZ,k) = argmax score(X->YZ) *
                      bestScore(Y,i,k,s) *
                      bestScore(Z,k,j,s)
   parse.parent = X
   parse.leftChild = bestParse(Y,i,k,s)
   parse.rightChild = bestParse(Z,k,j,s)
   return parse
```

A Recursive Parser

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

- Will this parser work?
- Why or why not?
- Memory requirements?

A Memoized Parser

- One small change:

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

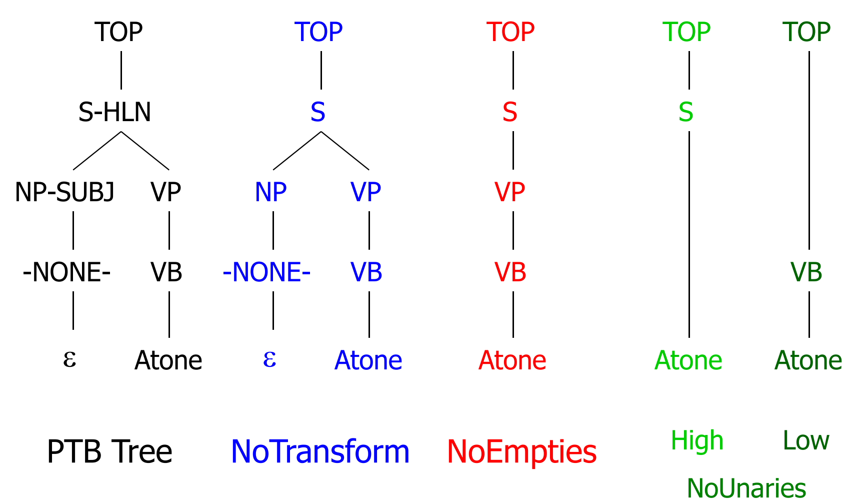
Memory: Theory

- How much memory does this require?
  - Have to store the score cache
  - Cache size: |symbols|*n^2 doubles
  - For the plain treebank grammar:
    - X ~ 20K, n = 40, double ~ 8 bytes = ~ 256MB
    - Big, but workable.
- What about sparsity?

Time: Theory

- How much time will it take to parse?
  - Have to fill each cache element (at worst)
  - Each time the cache fails, we have to:
    - Iterate over each rule $X \rightarrow Y\ Z$ and split point k
    - Do constant work for the recursive calls
  - Total time: $|rules|*n^3$
  - Cubic time
  - Something like 5 sec for an unoptimized parse of a 20-word sentences

Unaries in Grammars



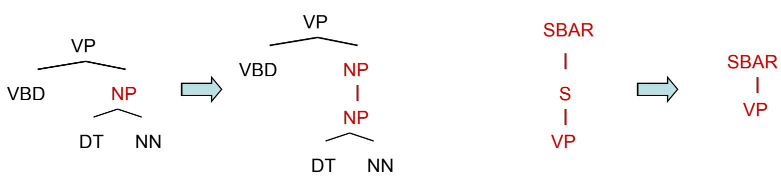
Unary Rules

- Unary rules?

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

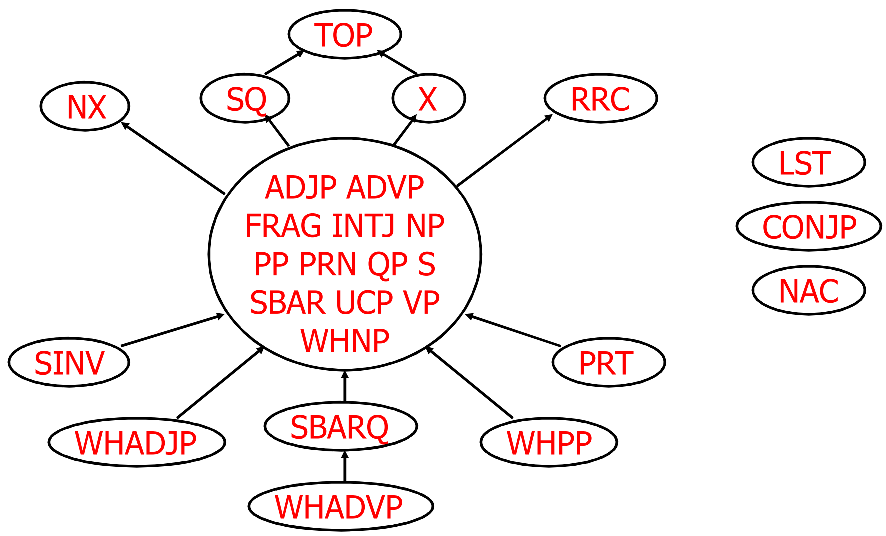
CNF + Unary Closure

- We need unaries to be non-cyclic
  - Can address by pre-calculating the *unary closure*
  - Rather than having zero or more unaries, always have exactly one



  - Alternate unary and binary layers
  - Reconstruct unary chains afterwards

Same-Span Reachability



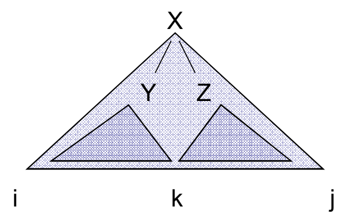
Alternating Layers

```
bestScoreB(X,i,j,s)
      return max max score(X->YZ) *
                     bestScoreU(Y,i,k) *
                     bestScoreU(Z,k,j)



bestScoreU(X,i,j,s)
   if (j = i+1)
       return tagScore(X,s[i])
   else
       return max max score(X->Y) *
                      bestScoreB(Y,i,j)
```

A Bottom-Up Parser (CKY)

- Can also organize things bottom-up

```
bestScore(s)
  for (i : [0,n-1])
    for (X : tags[s[i]])
      score[X][i][i+1] =
          tagScore(X,s[i])
  for (diff : [2,n])
    for (i : [0,n-diff])
      j = i + diff
      for (X->YZ : rule)
        for (k : [i+1, j-1])
          score[X][i][j] = max score[X][i][j],
                               score(X->YZ) *
                               score[Y][i][k] *
                               score[Z][k][j]
```



Efficient CKY

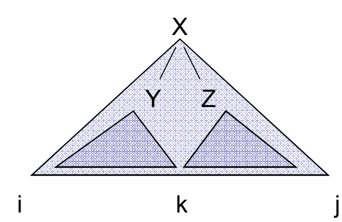
- Lots of tricks to make CKY efficient
  - Most of them are little engineering details:
    - E.g., first choose k, then enumerate through the Y:[i,k] which are non-zero, then loop through rules by left child.
    - Optimal layout of the dynamic program depends on grammar, input, even system details.
  - Another kind is more critical:
    - Many X:[i,j] can be suppressed on the basis of the input string
    - We'll see this next class as figures-of-merit or A* heuristics

Memory: Practice

- Memory:
  - Still requires memory to hold the score table
- Pruning:
  - score[X][i][j] can get too large (when?)
  - can instead keep beams scores[i][j] which only record scores for the top K symbols found to date for the span [i,j]

Time: Theory

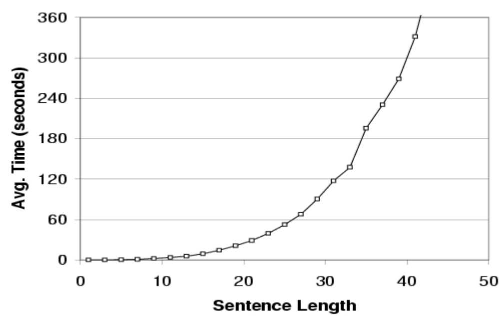
- How much time will it take to parse?
  - For each diff (<= n)
    - For each i (<= n)
      - For each rule X → Y Z
        - For each split point k
          Do constant work



  - Total time: |rules|*n^3

Runtime: Practice

- Parsing with the vanilla treebank grammar:



~ 20K Rules

(not an optimized parser!)

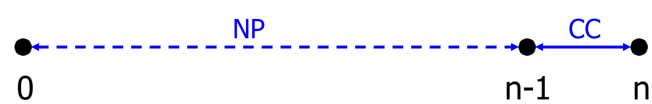
Observed exponent:

3.6

- Why's it worse in practice?
  - Longer sentences "unlock" more of the grammar
  - All kinds of systems issues don't scale

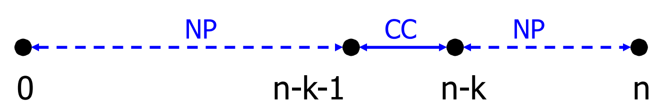
Rule State Reachability

Example: NP CC •



1 Alignment

Example: NP CC NP •



n Alignments

- Many states are more likely to match larger spans!