Natural Language Processing

Syntax and Parsing

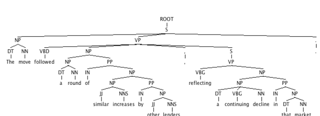
Dan Klein – UC Berkeley

1

Syntax

2

Parse Trees

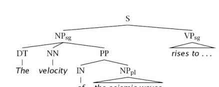


The move followed a round of similar increases by other lenders, reflecting a continuing decline in that market

3

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…

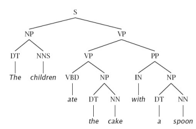


new art critics write reviews with computers

4

Constituency Tests

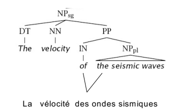
- How do we know what nodes go in the tree?
- Classic constituency tests:
  - Substitution by *proform*
  - Question answers
  - Semantic gounds
    - Coherence
    - Reference
    - Idioms
  - Dislocation
  - Conjunction
- Cross-linguistic arguments, too



5

Conflicting Tests

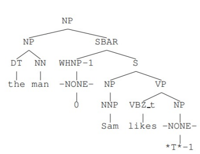
- Constituency isn't always clear
  - Units of transfer:
    - think about ~ penser à
    - talk about ~ hablar de
  - Phonological reduction:
    - I will go → I'll go
    - I want to go → I wanna go
    - a le centre → au centre
  - Coordination
    - He went to and came from the store.

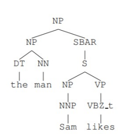


6

Structure Depth

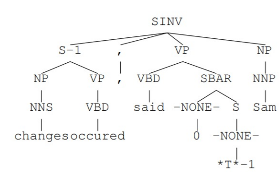
- Q: Do we model deep vs surface structure?





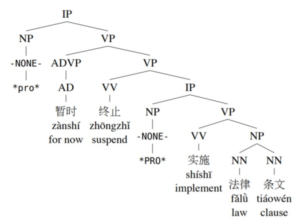
[Example: Johnson 02]

7



[Example: Johnson 02]

8



[Example: Cai et al 11]

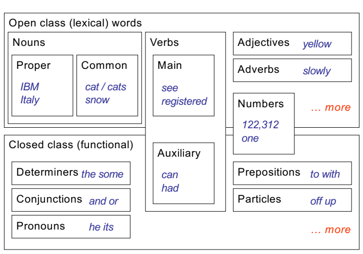
9

Ambiguities

10

Parts-of-Speech (English)

- One basic kind of linguistic structure: syntactic word classes



11

Part-of-Speech Ambiguity

- Words can have multiple parts of speech

Fed	raises	interest	rates	0.5	percent
VBD		VB			
VBN	VBZ	VBP	VBZ		
NNP	NNS	NN	NNS	CD	NN

Fed raises interest rates 0.5 percent

Mrs./NNP Shaefer/NNP never/RB got/VBD **around/RP** to/TO joining/VBG
All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB **around/IN** the/DT corner/NN
Chateau/NNP Petrus/NNP costs/VBZ **around/RB** 250/CD

- Two basic sources of constraint:
  - Grammatical environment
  - Identity of the current word
- Many more possible features:
  - Suffixes, capitalization, name databases (gazetteers), etc…

12

Why POS Tagging?

- Useful in and of itself (more than you'd think)
  - Text-to-speech: record, lead
  - Lemmatization: saw[v] → see, saw[n] → saw
  - Quick-and-dirty NP-chunk detection: grep {JJ | NN}* {NN | NNS}
- Useful as a pre-processing step for parsing
  - Less tag ambiguity means fewer parses
  - However, some tag choices are better decided by parsers

IN
DT NNP NN VBD VBN RP NN NNS
The Georgia branch had taken on loan commitments …

VDN
DT NN IN NN VBD NNS VBD
The average of interbank offered rates plummeted …

13

Classical NLP: Parsing

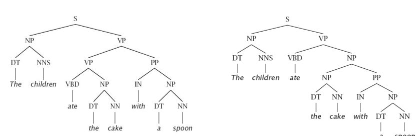
- Write symbolic or logical rules:

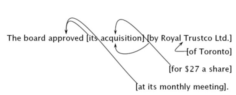
Grammar (CFG)		Lexicon
ROOT → S	NP → NP PP	NN → interest
S → NP VP	VP → VBP NP	NNS → raises
NP → DT NN	VP → VBP NP PP	VBP → interest
NP → NN NNS	PP → IN NP	VBZ → raises
		…

- 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

14

Ambiguities: PP Attachment





15

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

16

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.

17

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.

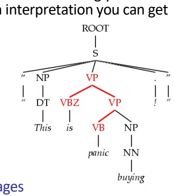
18

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

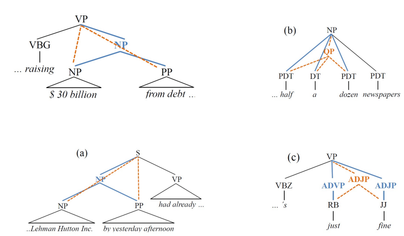
"This will panic buyers ! "



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

19

Ambiguities as Trees



20

PCFGs

21

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 $P(Y_1 Y_2 \ldots Y_k \mid X)$

22

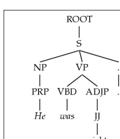
Treebank Sentences

```
( (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))))))
     .))
```

23

Treebank Grammars

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



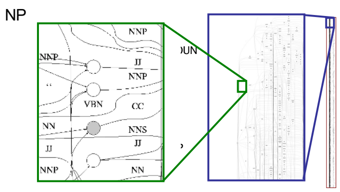
ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1
…..	

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

24

Treebank Grammar Scale

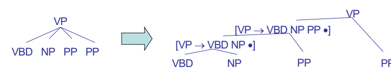
- Treebank grammars can be enormous
  - As FSAs, the raw grammar has ~10K states, excluding the lexicon
  - Better parsers usually make the grammars larger, not smaller



25

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!

26

CKY Parsing

27

A Recursive Parser

```
bestScore(X,i,j)
  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?

28

A Memoized Parser

- One small change:

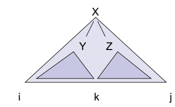
```
bestScore(X,i,j)
   if (scores[X][i][j] == null)
      if (j = i+1)
         score = tagScore(X,s[i])
      else
         score = max score(X->YZ) *
                     bestScore(Y,i,k) *
                     bestScore(Z,k,j)
      scores[X][i][j] = score
   return scores[X][i][j]
```

29

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]
```



30

Unary Rules

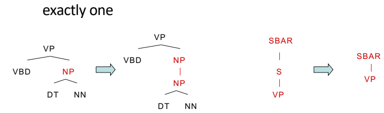
- Unary rules?

```
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)
```

31

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

32

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)
```

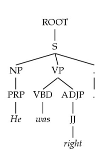
33

Learning PCFGs

34

Treebank PCFGs [Charniak 96]

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

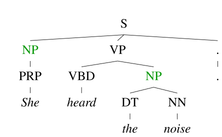


ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1
…..	

Model	*F1*
Baseline	72.0

35

Conditional Independence?

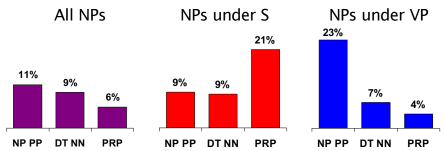


- Not every NP expansion can fill every NP slot
  - A grammar with symbols like "NP" won't be context-free
  - Statistically, conditional independence too strong

36

Non-Independence

- Independence assumptions are often too strong.

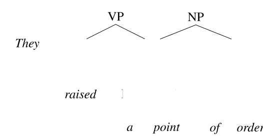


- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

37

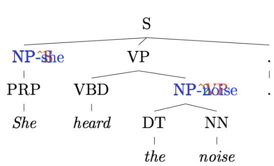
Grammar Refinement

- Example: PP attachment



38

Grammar Refinement



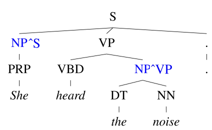
- Structure Annotation [Johnson '98, Klein&Manning '03]
- Lexicalization [Collins '99, Charniak '00]
- Latent Variables [Matsuzaki et al. 05, Petrov et al. '06]

39

Structural Annotation

40

The Game of Designing a Grammar



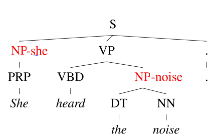
- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Structural annotation

41

Lexicalization

43

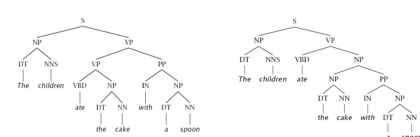
The Game of Designing a Grammar



- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Structural annotation [Johnson '98, Klein and Manning 03]
  - Head lexicalization [Collins '99, Charniak '00]

44

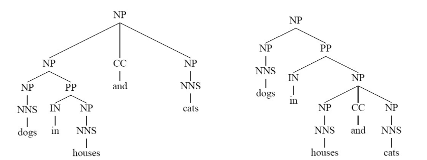
Problems with PCFGs



- 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

45

Problems with PCFGs

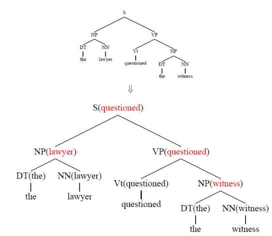


- What's different between basic PCFG scores here?
- What (lexical) correlations need to be scored?

46

Lexicalized Trees

- Add "head words" 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



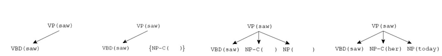
47

Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

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

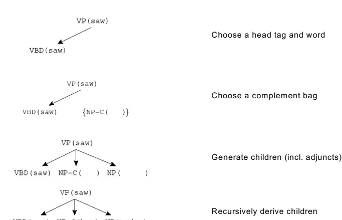
- Never going to get these atomically off of a treebank
- Solution: break up derivation into smaller steps



48

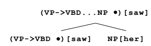
Lexical Derivation Steps

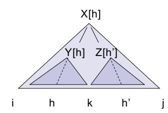
- A derivation of a local tree [Collins 99]



49

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,h',X->YZ
              bestScore(Y,i,k,h) *
              bestScore(Z,k,j,h')
          max score(X[h]->Y[h'] Z[h]) *
     k,h',X->YZ
              bestScore(Y,i,k,h') *
              bestScore(Z,k,j,h)
```

50

Results

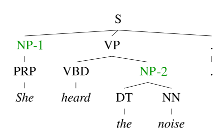
- Some results
  - Collins 99 – 88.6 F1 (generative lexical)
  - Charniak and Johnson 05 – 89.7 / 91.3 F1 (generative lexical / reranked)
  - Petrov et al 06 – 90.7 F1 (generative unlexical)
  - McClosky et al 06 – 92.1 F1 (gen + rerank + self-train)
- However
  - Bilexical counts rarely make a difference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

55

Latent Variable PCFGs

56

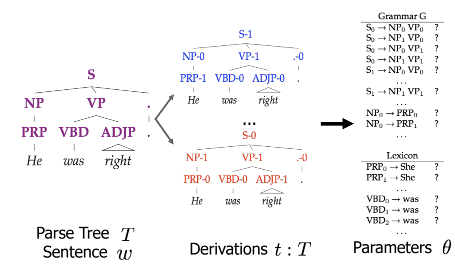
The Game of Designing a Grammar



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

59

Latent Variable Grammars

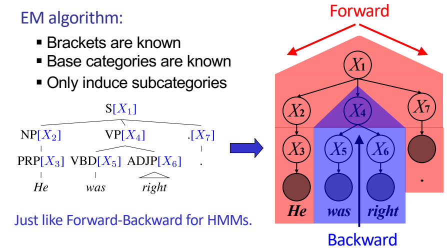


60

Learning Latent Annotations

EM algorithm:

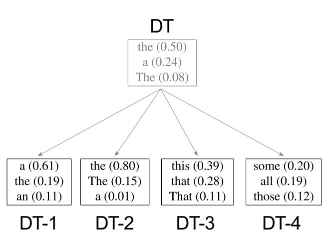
- Brackets are known
- Base categories are known
- Only induce subcategories



Just like Forward-Backward for HMMs.

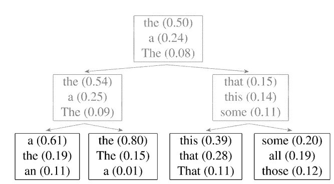
61

Refinement of the DT tag



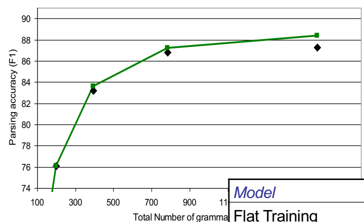
62

Hierarchical refinement



63

Hierarchical Estimation Results

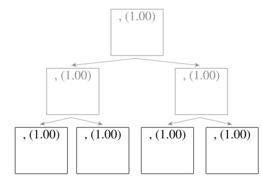


Model	*F1*
Flat Training	87.3
Hierarchical Training	88.4

64

Refinement of the , tag

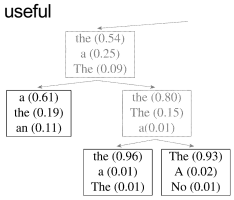
- Splitting all categories equally is wasteful:



65

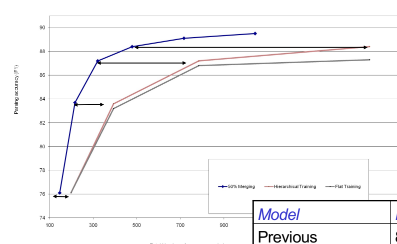
Adaptive Splitting

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



66

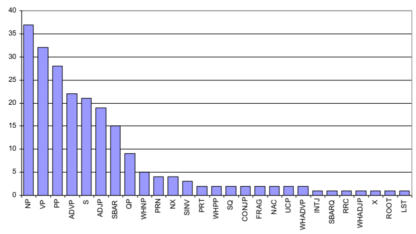
Adaptive Splitting Results



Model	*F1*
Previous	88.4
With 50% Merging	89.5

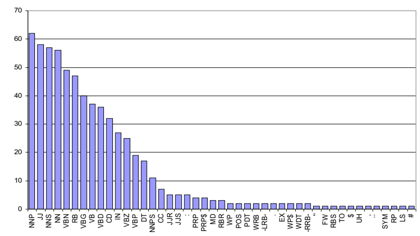
67

Number of Phrasal Subcategories



68

Number of Lexical Subcategories



69

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

70

Learned Splits

- Relative adverbs (RBR):

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

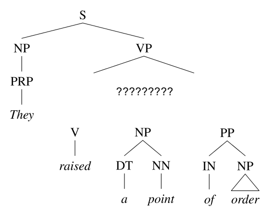
- Cardinal Numbers (CD):

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

71

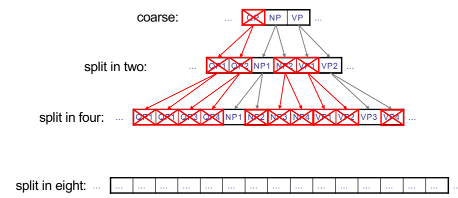
Coarse-to-Fine Inference

- Example: PP attachment



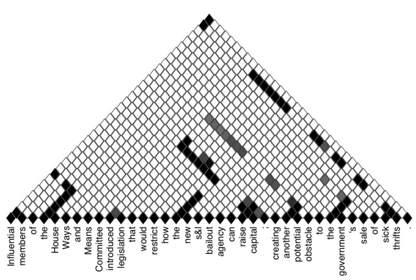
72

Hierarchical Pruning



73

Bracket Posteriors



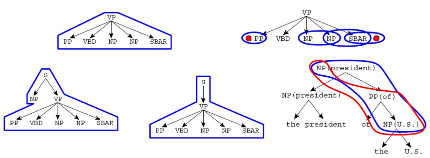
74

Other Syntactic Models

75

Parse Reranking

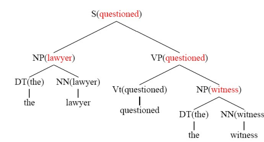
- Assume the number of parses is very small
- We can represent each parse T as a feature vector φ(T)
  - Typically, all local rules are features
  - Also non-local features, like how right-branching the overall tree is
  - [Charniak and Johnson 05] gives a rich set of features

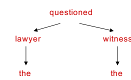


76

Dependency Parsing

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



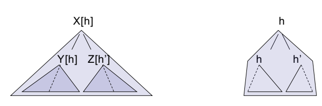


- Each local binary tree corresponds to an attachment in the dependency graph

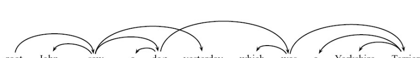
78

Dependency Parsing

- Pure dependency parsing is only cubic [Eisner 99]



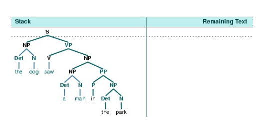
- Some work on *non-projective* dependencies
  - Common in, e.g. Czech parsing
  - Can do with MST algorithms [McDonald and Pereira 05]



79

Shift-Reduce Parsers

- Another way to derive a tree:

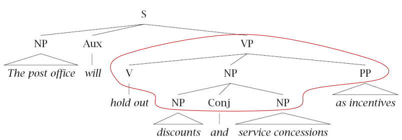


- Parsing
  - No useful dynamic programming search
  - Can still use beam search [Ratnaparkhi 97]

80

Data-oriented parsing:

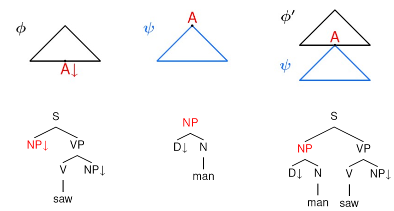
- Rewrite large (possibly lexicalized) subtrees in a single step



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

81

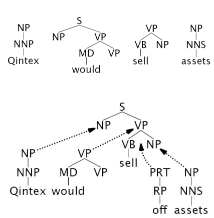
TIG: Insertion



82

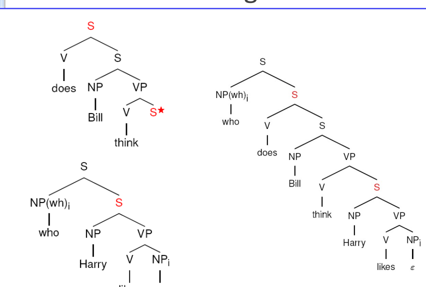
Tree-adjoining grammars

- 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)



83

TAG: Long Distance



84

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?)

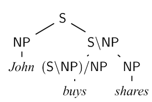
$John \vdash \mathsf{NP}$

$shares \vdash \mathsf{NP}$

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

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

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



85