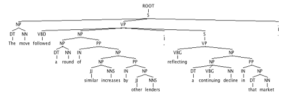
# Natural Language Processing


Syntax and Parsing

Dan Klein – UC Berkeley

# Syntax

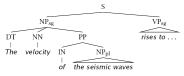
## Parse Trees



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

## Phrase Structure Parsing

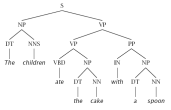
- Phrase structure parsing organizes syntax into *constituents* or *brackets*
- In general, this involves nested trees
- Linguists can, and do, argue about details
- Lots of ambiguity
- Not the only kind of syntax…




new art critics write reviews with computers

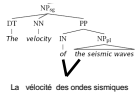
## Constituency Tests

- 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

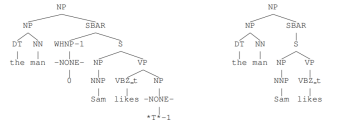
- Constituency isn't always clear
  - Units of transfer:
    - think about ~ penser à
    - talk about ~ hablar de
  - Phonological reduction:
    - I will go → I'll go
    - I want to go → I wanna go
    - a le centre → au centre
  - Coordination
    - He went to and came from the store.



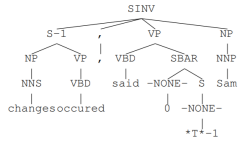

La vélocité des ondes sismiques

## Structure Depth

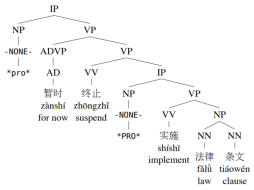
- Q: Do we model deep vs surface structure?




[Example: Johnson 02]




[Example: Johnson 02]

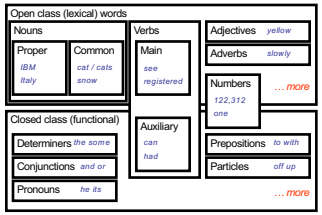



[Example: Cai et al 11]

## Ambiguities

## Parts-of-Speech (English)

- One basic kind of linguistic structure: syntactic word classes




## Part-of-Speech Ambiguity

- Words can have multiple parts of speech

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…

## Why POS Tagging?

- Historically 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 …

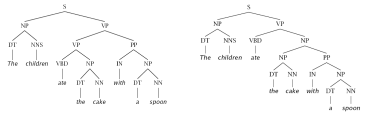
## Classical NLP: Parsing

- 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

## Ambiguities: PP Attachment





## 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

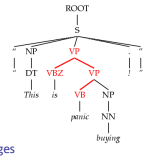
- Modifier scope within NPs
  *impractical design requirements*
  *plastic cup holder*
- Multiple gap constructions
  *The chicken is ready to eat.*
  *The contractors are rich enough to sue.*
- Coordination scope:
  *Small rats and mice can squeeze into holes or cracks in the wall.*

## Inaccessible Ambiguities

- *Inaccessible 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

## PCFGs

## Probabilistic Context-Free Grammars

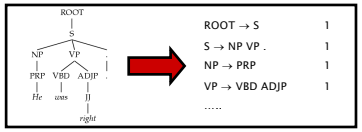
- A context-free grammar is a tuple *<N, T, S, R>*
  - *N* : the set of non-terminals
    - Phrasal categories: S, NP, VP, ADJP, etc.
    - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
  - *T* : the set of terminals (the words)
  - *S* : the start symbol
    - Often written as ROOT or TOP
    - *Not* 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 → NP VP, VP → 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

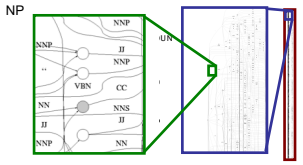
- Need a PCFG for broad coverage parsing.
- Can take a grammar right off the trees (doesn't work well):




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

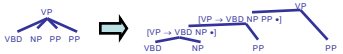
## Treebank Grammar Scale

- 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



## 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!

## CKY Parsing

## 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?

## A Memoized Parser

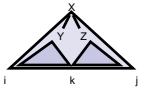
- One small change:

```
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]
```

## 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]
```



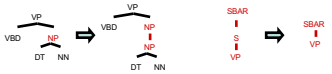

## Unary Rules

- 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

## Alternating Layers

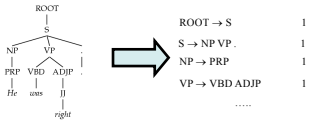
```
bestScoreB(X,i,j,s)
    return max max score(X->YZ) *
                 bestScoreU(Y,i,k) *
                 bestScoreU(Z,k,j)


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)
```

## Learning PCFGs

## Treebank PCFGs [Charniak 96]

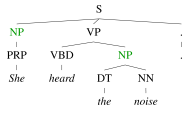
- Use PCFGs for broad coverage parsing
- Can take a grammar right off the trees (doesn't work well):




| | |
|---|---|
| ROOT → S | 1 |
| S → NP VP . | 1 |
| NP → PRP | 1 |
| VP → VBD ADJP | 1 |
| ..... | |

| Model | F1 |
|---|---|
| Baseline | 72.0 |

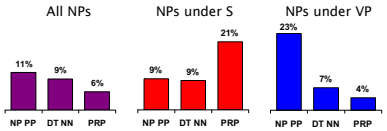
## Conditional Independence?




- 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

## Non-Independence

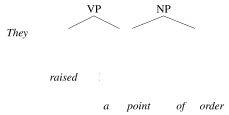
- Independence assumptions are often too strong.




- 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!

## Grammar Refinement

- Example: PP attachment

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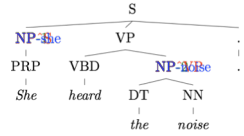
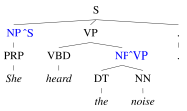
## Grammar Refinement




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

## Structural Annotation

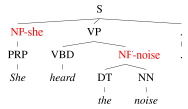
## The Game of Designing a Grammar




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

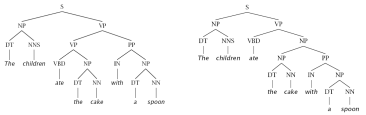
## Lexicalization

## The Game of Designing a Grammar



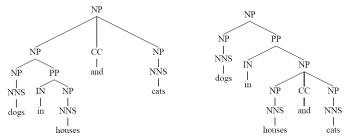

- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Structural annotation [Johnson '98, Klein and Manning 03]
  - Head lexicalization [Collins '99, Charniak '00]

## 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

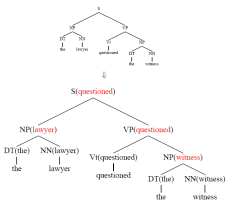
## Problems with PCFGs



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

## 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




## Lexicalized PCFGs?

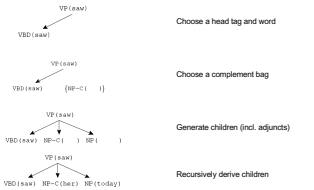
- Problem: we now have to estimate probabilities like

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

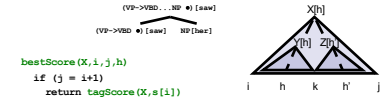
- Never going to get these atomically off of a treebank
- Solution: break up derivation into smaller steps

## Lexical Derivation Steps

- A derivation of a local tree [Collins 99]



## Lexicalized CKY







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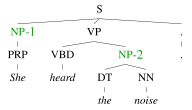

## Results

- 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

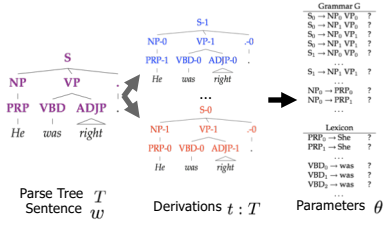
## Latent Variable PCFGs

## The Game of Designing a Grammar




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

## Latent Variable Grammars




Parse Tree $T$
Sentence $w$

Derivations $t : T$

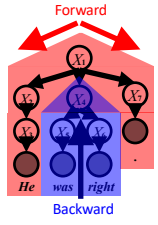
Parameters $\theta$

## Learning Latent Annotations

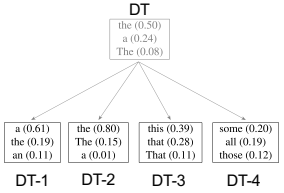
EM algorithm:

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

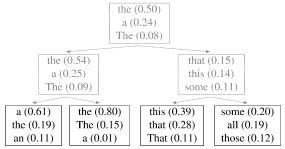

Just like Forward-Backward for HMMs.



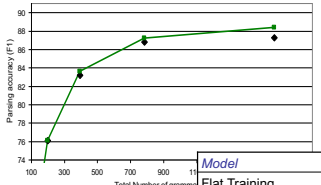
## Refinement of the DT tag




## Hierarchical refinement



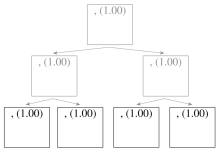

## Hierarchical Estimation Results




| Model | F1 |
|---|---|
| Flat Training | 87.3 |
| Hierarchical Training | 88.4 |

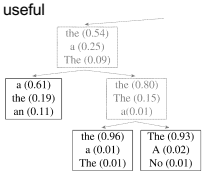
## Refinement of the , tag

- Splitting all categories equally is wasteful:

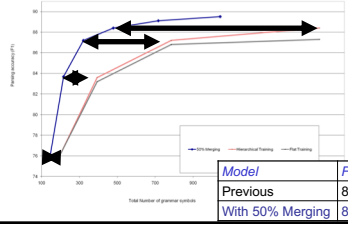



## Adaptive Splitting

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

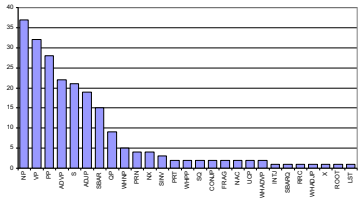



## Adaptive Splitting Results

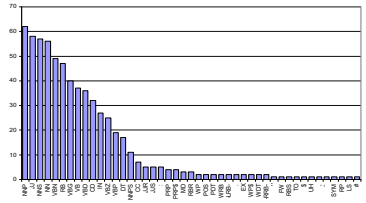


| Model | F1 |
|---|---|
| Previous | 88.4 |
| With 50% Merging | 89.5 |

## 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

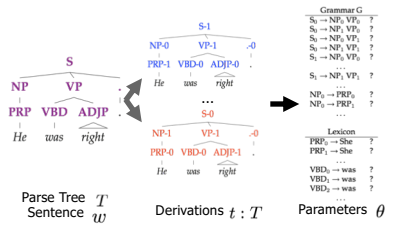
- Relative adverbs (RBR):

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

- Cardinal Numbers (CD):

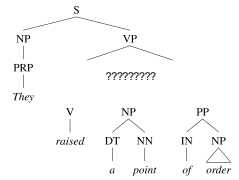
| | | | |
|---|---|---|---|
| CD-7 | one | two | Three |
| CD-4 | 1989 | 1990 | 1988 |
| CD-11 | million | billion | trillion |
| CD-0 | 1 | 50 | 100 |
| CD-3 | 1 | 30 | 31 |
| CD-9 | 78 | 58 | 34 |

## Latent Variable Grammars

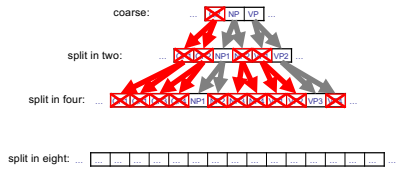



## Coarse-to-Fine Inference

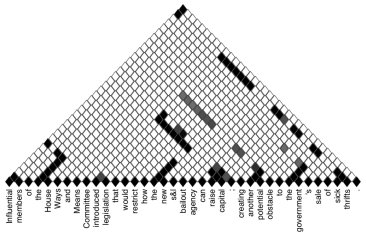
- Example: PP attachment



## Hierarchical Pruning

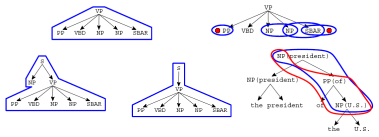



## Bracket Posteriors



## 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



# Natural Language Processing

Berkeley NLP

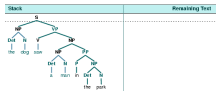
Syntax and Parsing

Dan Klein – UC Berkeley

# Other Syntactic Models

## Shift-Reduce Parsers

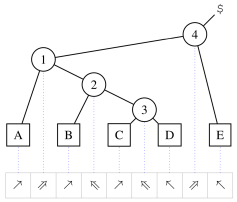
- Another way to derive a tree:



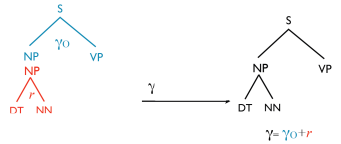
- Parsing
  - No useful dynamic programming search
  - Can still use beam search [Ratnaparkhi 97]

## Other Transformations

- Example: Left-Corner Transforms, Tetra-Tags




## 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

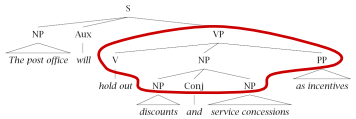
## Dependency Parsing

- 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]

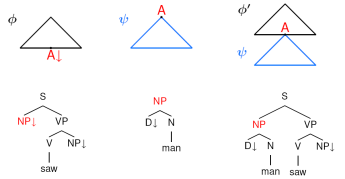

## Data-oriented parsing:

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



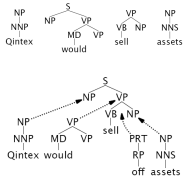

- Formally, a *tree-insertion grammar*
- Derivational ambiguity whether subtrees were generated atomically or compositionally
- Most probable *parse* is NP-complete

## TIG: Insertion

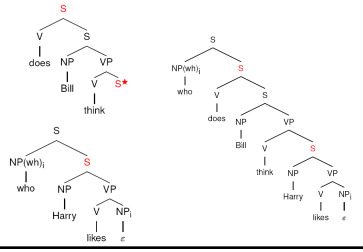


## Tree-adjoining grammars

- 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?)

$John \vdash \mathrm{NP}$

$shares \vdash \mathrm{NP}$

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

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

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