Statistical Parsing

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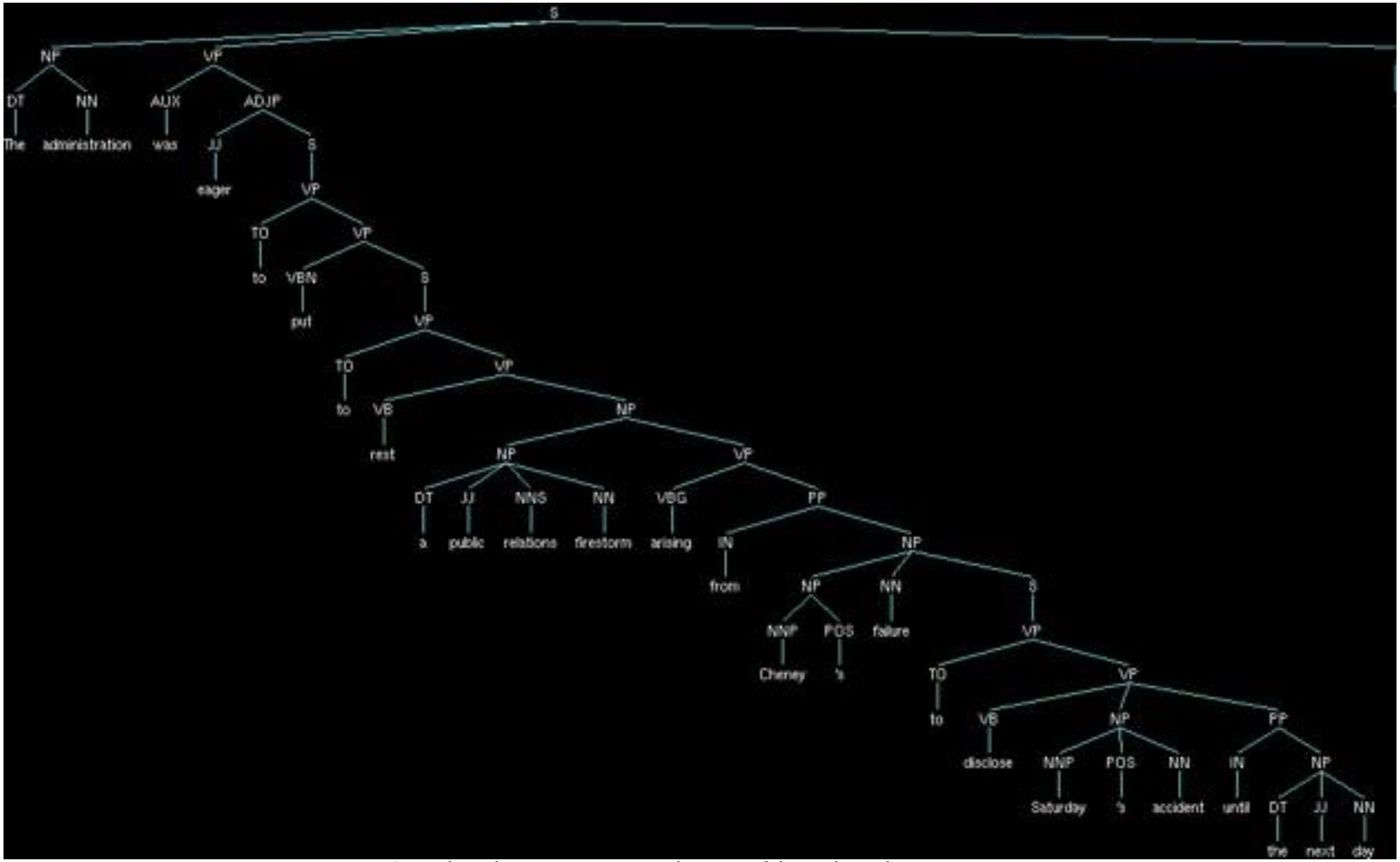
for CSI 5386 @ uOttawa

- Statistical parsing
- Sources of problems
- Improvements
  - Grammar rewriting
  - Lexicalized grammars

CFG Parsing

- We left CFG parsing (CKY) with the problem of selecting the “right” parse out of all the possible parses...
- Now if we define “right” parse as “most probable parse” we get our old friend
    - Argmax P(Parse|Words)

Example


S
NP
VP
DT
NN
AUX
ADJP
The
administration
was
JJ
S
eager
VP
TO
VP
to
VBN
S
put
VP
TO
VP
to
VB
NP
rest
NP
VP
DT
JJ
NNS
NN
VBG
PP
a
public
relations
firestorm
arising
IN
NP
from
NP
NN
S
NNP
POS
failure
VP
Cheney
's
TO
VP
to
VB
NP
PP
disclose
NNP
POS
NN
IN
NP
Saturday
's
accident
until
DT
JJ
NN
the
next
day

Probabilistic CFGs

1 The framework (Model)

- How to assign probabilities to parse trees

2 Training the model (Learning)

- How to acquire estimates for the probabilities specified by the model

3 Parsing with probabilities (Decoding)

- Given an input sentence and a model how can we efficiently find the best (or *N* best) tree(s) for that input

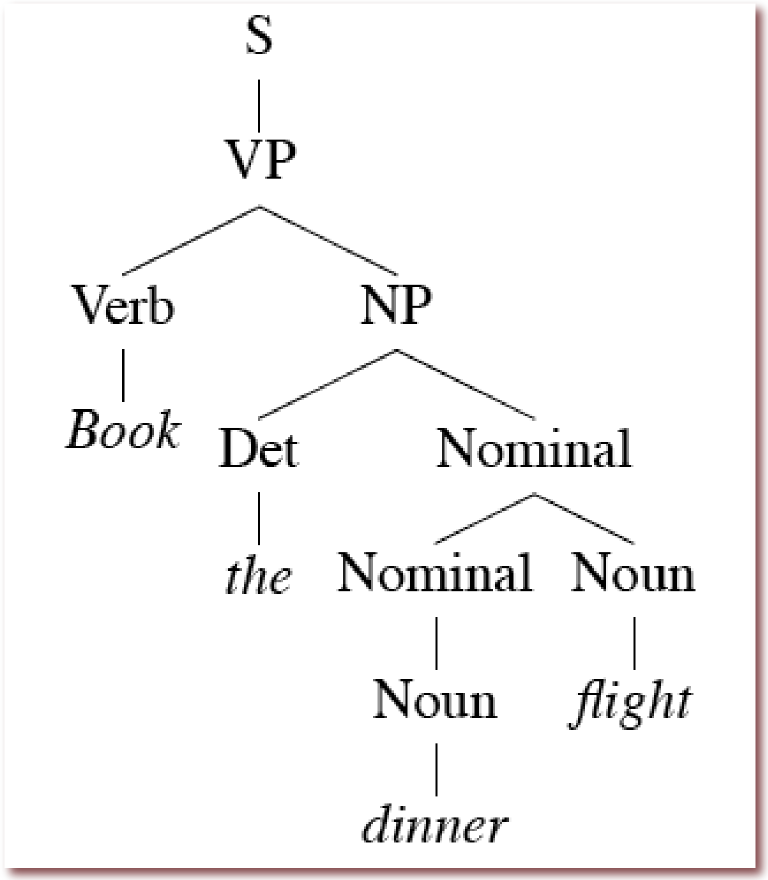
Simple Probability Model

- A derivation (tree) consists of the collection of grammar rules that are in the tree
  - The probability of a tree is the product of the probabilities of the rules in the derivation.

$$P(T,S) = \prod_{node \in T} P(rule(n))$$

Example

- How many "rules" are in this derivation?



Rule Probabilities

- So… What's the probability of a rule?
- Start at the top...
  - A tree should have an *S* at the top. So given that we know we need an *S*, we can ask about the probability of each particular *S* rule in the grammar.
    - That is P(particular S rule | S is what I need)
- So in general we need

$$P(\alpha \rightarrow \beta \mid \alpha)$$

For each rule in the grammar

Training the Model

- We can get the estimates we need from an annotated database (i.e., a treebank)

$$P(\alpha \rightarrow \beta|\alpha) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\sum_{\gamma}\text{Count}(\alpha \rightarrow \gamma)} = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

  - For example, to get the probability for a particular *VP* rule, just count all the times the rule is used and divide by the number of *VP*s overall.

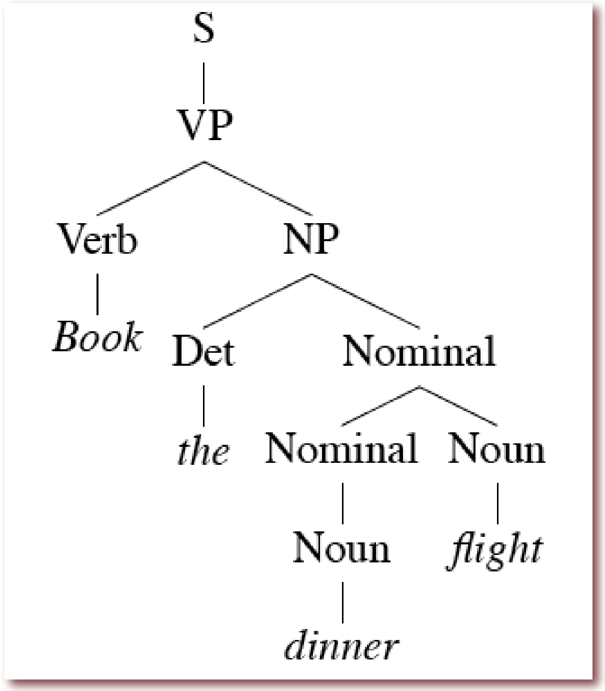
Parsing (Decoding)

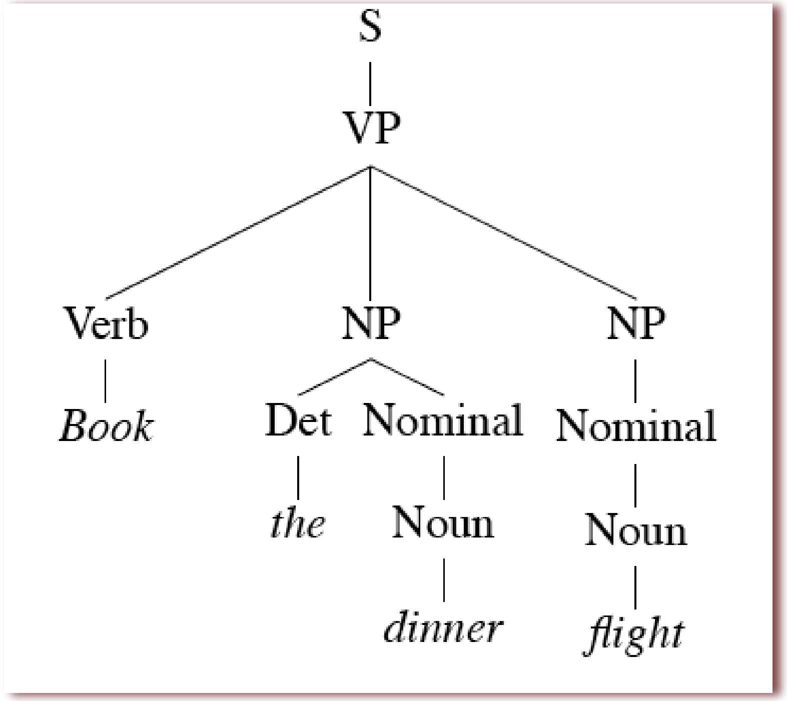
- So to get the best (most probable) parse for a given input

1. Enumerate all the trees for a sentence
2. Assign a probability to each using the model
3. Return the best (argmax)

Example

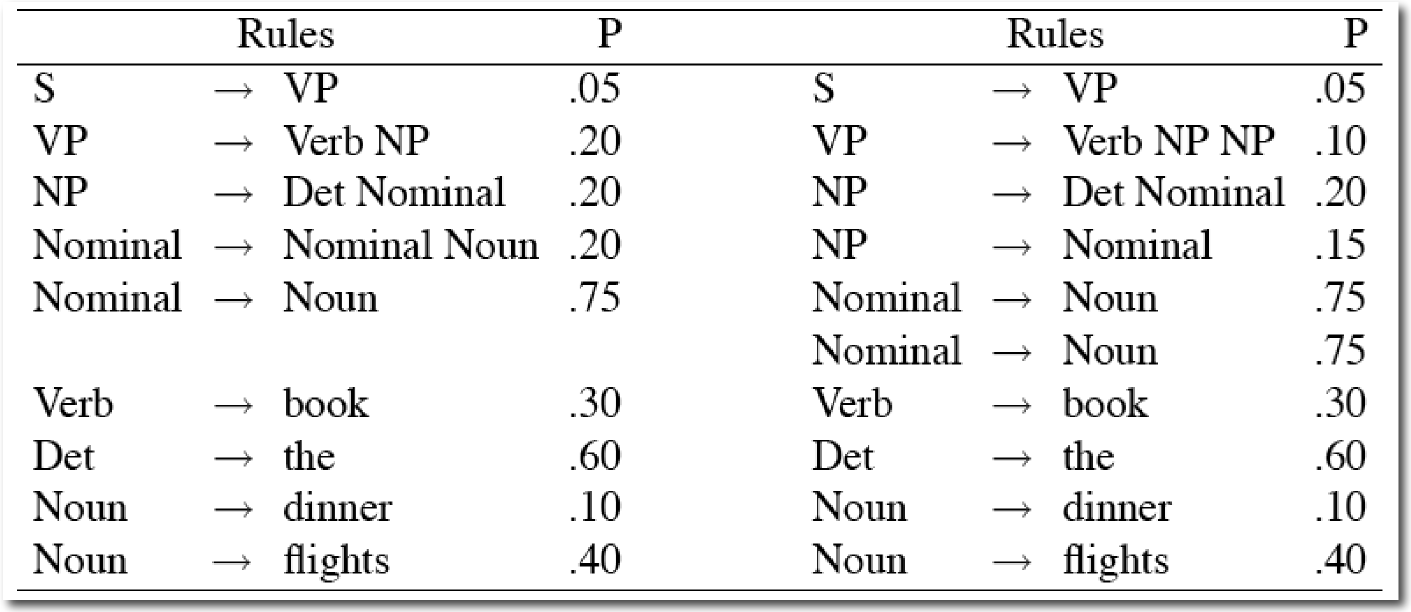
- Consider...
  - *Book the dinner flight*





Examples

- These trees consist of the following rules.



Rules			P	Rules			P
S	$\rightarrow$	VP	.05	S	$\rightarrow$	VP	.05
VP	$\rightarrow$	Verb NP	.20	VP	$\rightarrow$	Verb NP NP	.10
NP	$\rightarrow$	Det Nominal	.20	NP	$\rightarrow$	Det Nominal	.20
Nominal	$\rightarrow$	Nominal Noun	.20	NP	$\rightarrow$	Nominal	.15
Nominal	$\rightarrow$	Noun	.75	Nominal	$\rightarrow$	Noun	.75
				Nominal	$\rightarrow$	Noun	.75
Verb	$\rightarrow$	book	.30	Verb	$\rightarrow$	book	.30
Det	$\rightarrow$	the	.60	Det	$\rightarrow$	the	.60
Noun	$\rightarrow$	dinner	.10	Noun	$\rightarrow$	dinner	.10
Noun	$\rightarrow$	flights	.40	Noun	$\rightarrow$	flights	.40

$$
\begin{aligned}
P(T_{left}) &= .05 * .20 * .20 * .20 * .75 * .30 * .60 * .10 * .40 = \mathbf{2.2 \times 10^{-6}} \\
P(T_{right}) &= .05 * .10 * .20 * .15 * .75 * .75 * .30 * .60 * .10 * .40 = \mathbf{6.1 \times 10^{-7}}
\end{aligned}
$$

Dynamic Programming

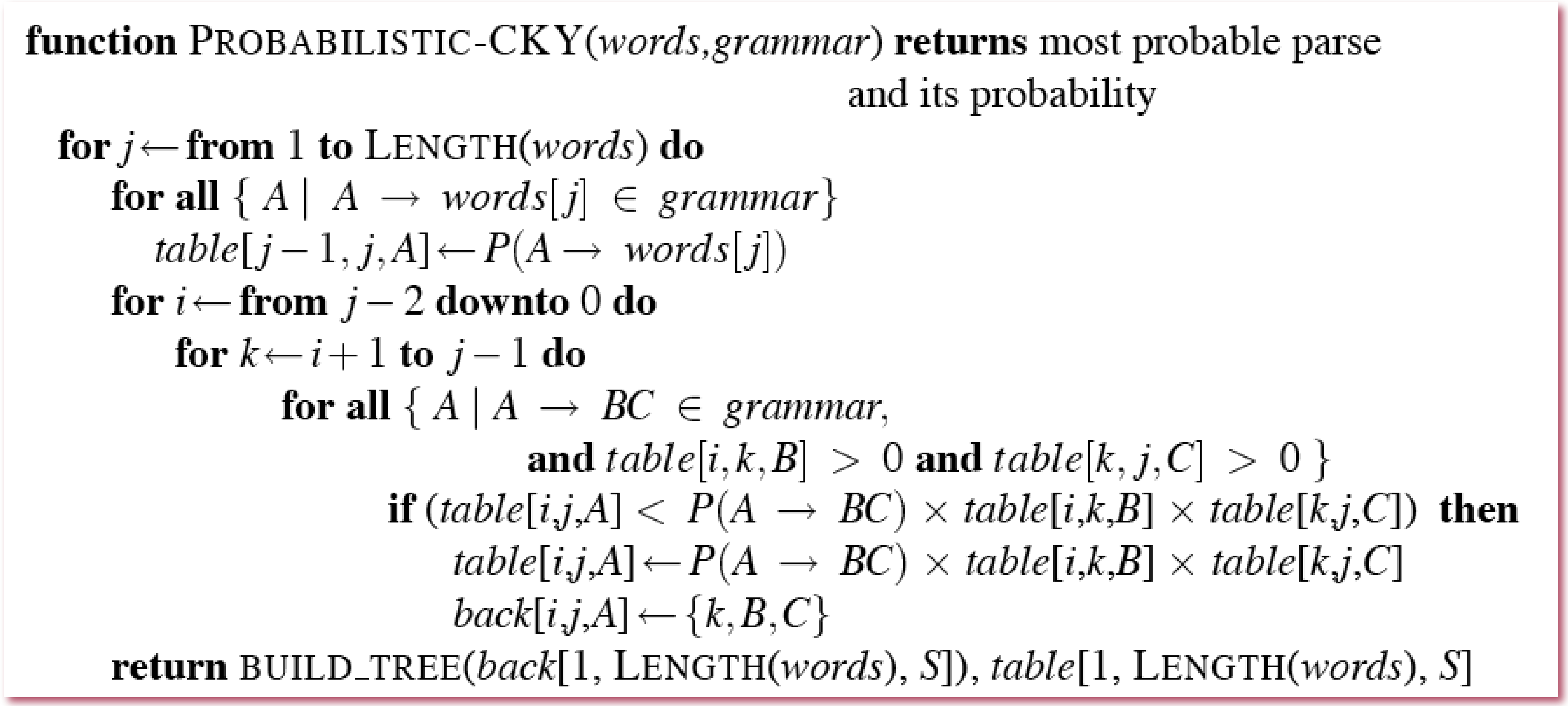
- Of course, as with normal parsing we don’t really want to do it that way...

- Instead, we need to exploit dynamic programming
  - For the parsing (as with CKY)
  - And for computing the probabilities and returning the best parse (as with Viterbi and HMMs)

Probabilistic CKY

- Alter CKY so that the probabilities of constituents are stored in the table as they are derived
  - Probability of a new constituent *A* derived from the rule $A \rightarrow B\ C$:
    - $P(A \rightarrow B\ C \mid A) * P(B) * P(C)$
    - Where P(B) and P(C) are already in the table given the way that CKY operates
    - What we store is the MAX probability over all the A rules.

Probabilistic CKY



```
function PROBABILISTIC-CKY(words,grammar) returns most probable parse
                                                and its probability
  for $j \leftarrow$ from 1 to LENGTH(words) do
      for all $\{ A \mid A \rightarrow words[j] \in grammar \}$
         $table[j-1, j, A] \leftarrow P(A \rightarrow words[j])$
      for $i \leftarrow$ from $j-2$ downto 0 do
          for $k \leftarrow i+1$ to $j-1$ do
               for all $\{ A \mid A \rightarrow BC \in grammar,$
                        and $table[i,k,B] > 0$ and $table[k,j,C] > 0 \}$
                   if $(table[i,j,A] < P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C])$ then
                      $table[i,j,A] \leftarrow P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]$
                      $back[i,j,A] \leftarrow \{k, B, C\}$
      return BUILD_TREE(back[1, LENGTH(words), S]), table[1, LENGTH(words), S]
```

Probabilistic CFGs

1 The framework (Model)

- Product of probabilities of rules in a derivation

2 Training the model (Learning)

- MLE counts derived from a treebank

3 Parsing with probabilities (Decoding)

- CKY with max probabilities added in

HW Questions

```
function VITERBI(observations of len T, state-graph of len N) returns best-path

    create a path probability matrix viterbi[N+2,T]
    for each state s from 1 to N do                                  ; initialization step
        $viterbi[s,1] \leftarrow a_{0,s} * b_s(o_1)$
        $backpointer[s,1] \leftarrow 0$
    for each time step t from 2 to T do                              ; recursion step
      for each $\boxed{\text{state } s \text{ from } 1 \text{ to } N \text{ do}}$
        $viterbi[s,t] \leftarrow \max_{s'=1}^{N} \boxed{viterbi[s',t-1] * a_{s',s} * b_s(o_t)}$
        $backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} \boxed{viterbi[s',t-1] * a_{s',s}}$
    $viterbi[q_F,T] \leftarrow \max_{s=1}^{N} \boxed{viterbi[s,T] * a_{s,q_F}}$            ; termination step
    $backpointer[q_F,T] \leftarrow \operatorname{argmax}_{s=1}^{N} \boxed{viterbi[s,T] * a_{s,q_F}}$            ; termination step
    return the backtrace path by following backpointers to states back in time from
$backpointer[q_F,T]$
```

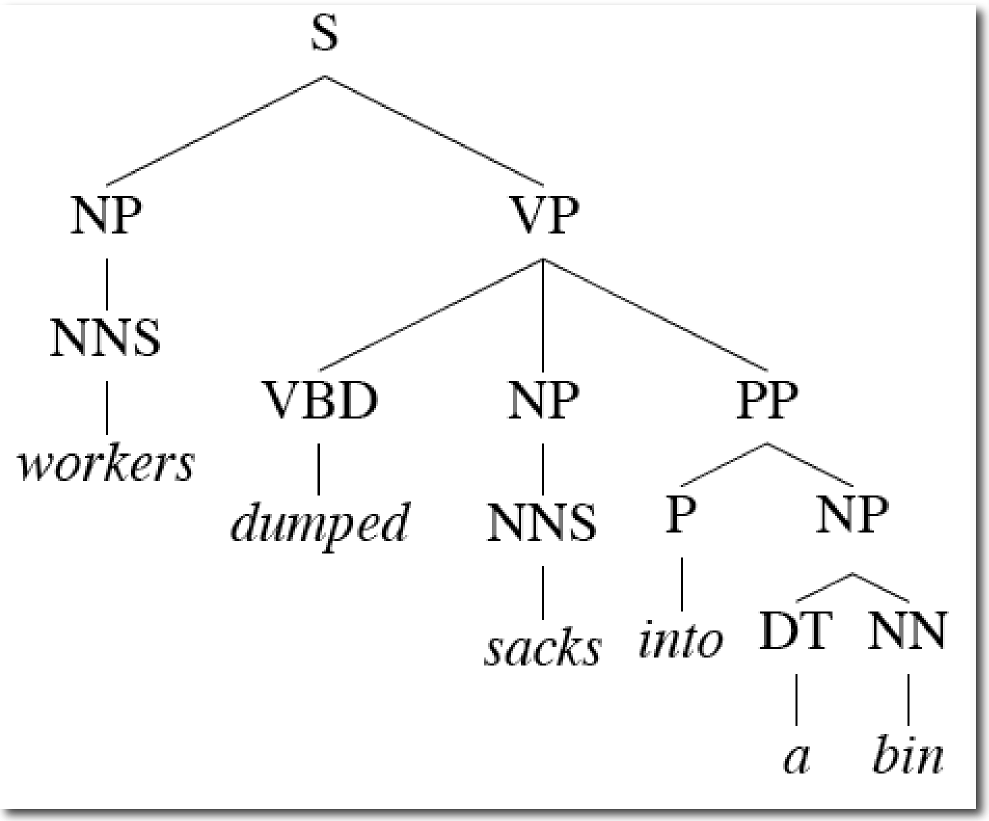
Problems with PCFGs

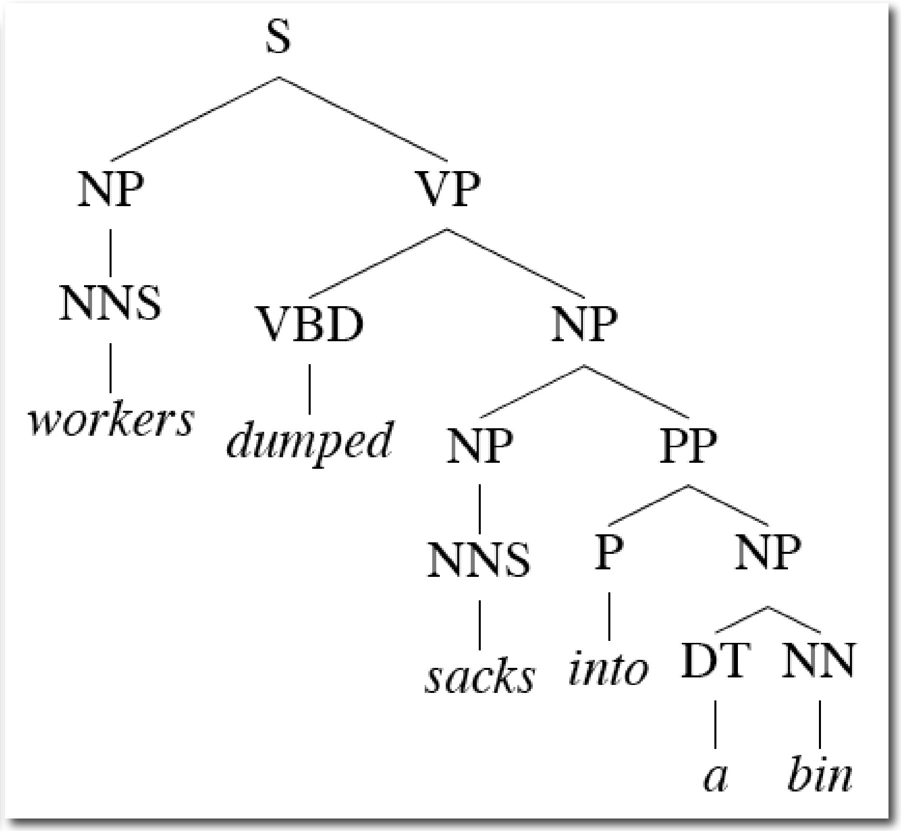
- The probability model we're using is just based on the the bag of rules in the derivation…
  1. Does not take the actual words into account in any useful way.
  2. Does not take into account *where* in the derivation a rule is used
  3. *Does not work terribly well*
     - That is, the most probable parse isn't usually the right one (the one in the treebank test set).

Common Sources of Problems

- Attachment ambiguities
  - PP attachment
  - Coordination problems

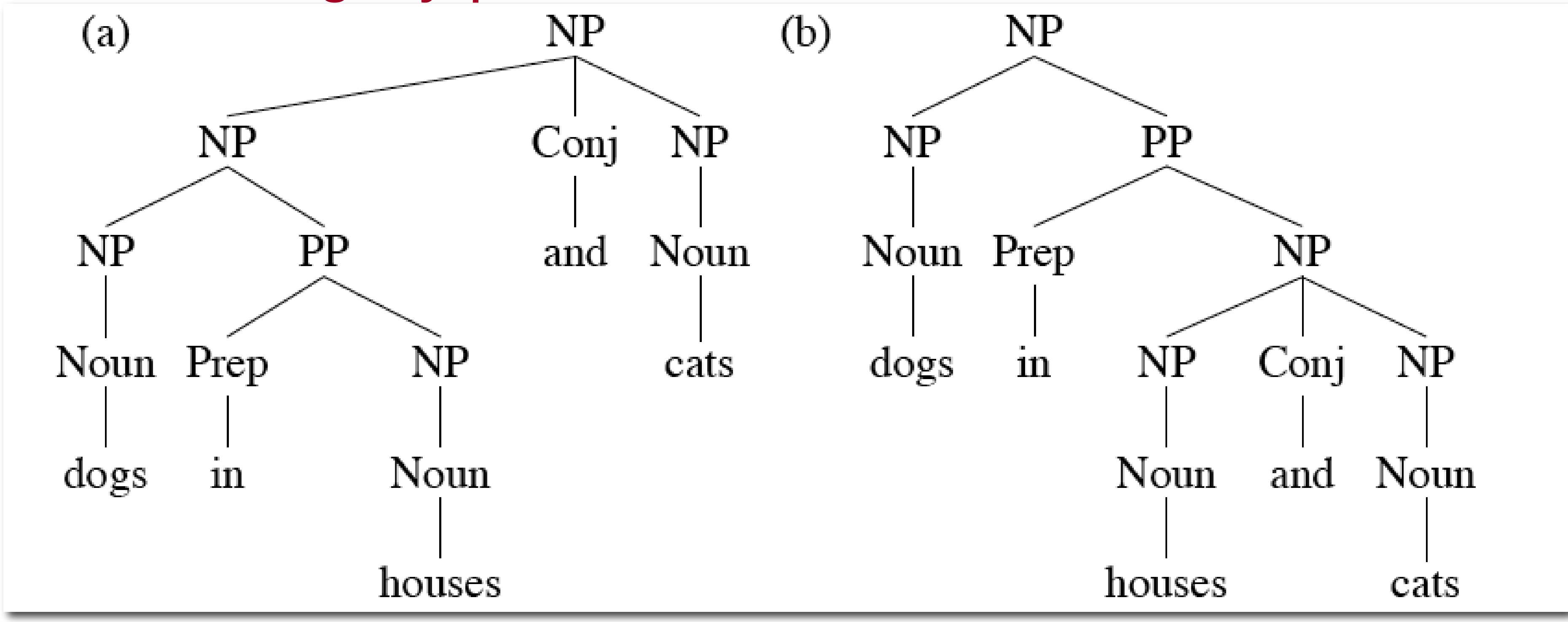
PP Attachment





Coordination

Most grammars have a rule (implicitly) of the form
X -> X and X. This leads to massive ambiguity problems.



Improved Approaches

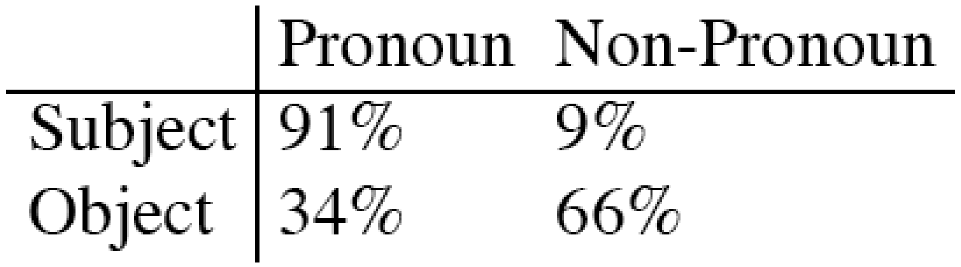
- There are two approaches to overcoming these shortcomings
  1. Rewrite the grammar to better capture the dependencies among rules
  2. Integrate lexical dependencies into the model
     1. And come up with the independence assumptions needed to make it work.

Solution 1: Rule Rewriting

- The grammar rewriting approach attempts to capture local tree information by rewriting the grammar so that the rules capture the regularities we want.
  - By splitting and merging the non-terminals in the grammar
  - Example: split NPs into different classes… that is, split the NP rules into separate rules

Example: NPs

- Our CFG rules for NPs don't condition on where in a tree the rule is applied
- But we know that not all the rules occur with equal frequency in all contexts.
  - Consider *NP*s that involve pronouns vs. those that don't.



	Pronoun	Non-Pronoun
Subject	91%	9%
Object	34%	66%

Example: NPs

- So that comes down to
  - NP --> Pronoun
- Gets replaced with something like
  - NP_Subj --> Pronoun
  - NP_Obj --> Pronoun

Separate rules, with different counts in the treebank and therefore different probabilities

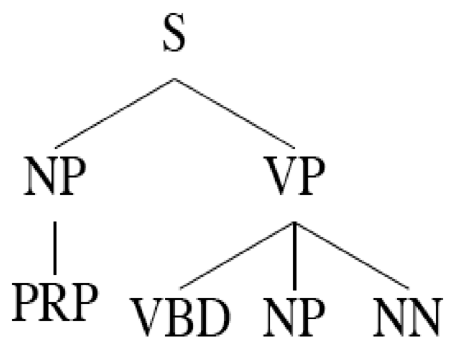
Rule Rewriting

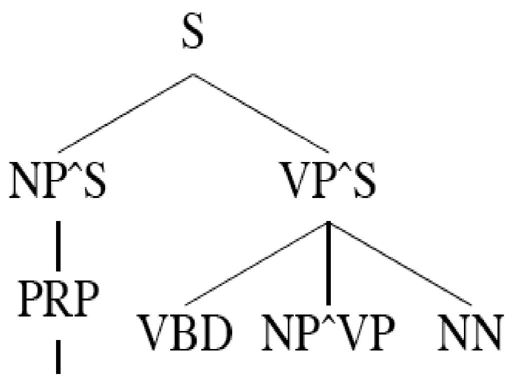
- Three approaches
  1. Use linguistic knowledge to directly rewrite rules by hand
     1. NP_Obj and the NP_Subj approach
  2. Automatically rewrite the rules using context to capture some of what we want
     1. Ie. Incorporate context into a context-free approach
  3. Search through the space of all rewrites for the grammar that maximizes the probability of the training set

Local Context Approach

- Condition the rules based on their parent nodes
  - Splitting based on tree-context captures some of the linguistic intuitions we saw with the NP example

Parent Annotation





- Now we have non-terminals NP^S and NP^VP that should capture the subject/object and pronoun/full NP cases. That is…
    - NP^S -> PRP
    - NP^VP -> DT
    - VP^S -> NP^VP

Auto Rewriting

- If this is such a good idea we may as well apply a learning approach to it.
- Start with a grammar (perhaps a treebank grammar)
- Search through the space of splits/merges for the grammar that in some sense maximizes parsing performance on the training/development set.

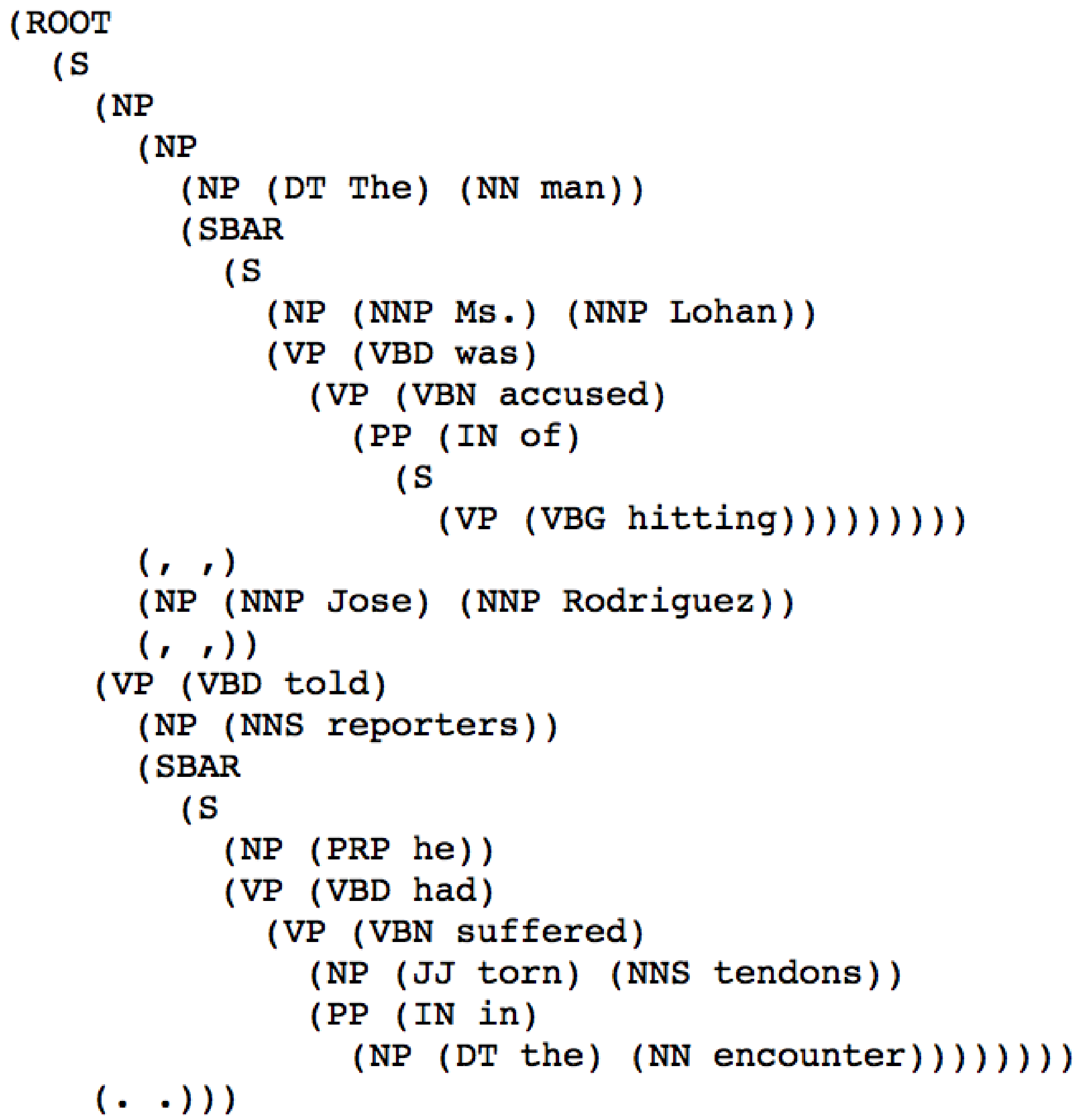
Auto Rewriting

- Basic idea…
  - Split every non-terminal into two new non-terminals across the entire grammar (X becomes X1 and X2).
  - Duplicate all the rules of the grammar that use X, dividing the probability mass of the original rule almost equally.
  - Run EM to readjust the rule probabilities
  - Perform a merge step to back off the splits that look like they don’t really do any good.

Demo

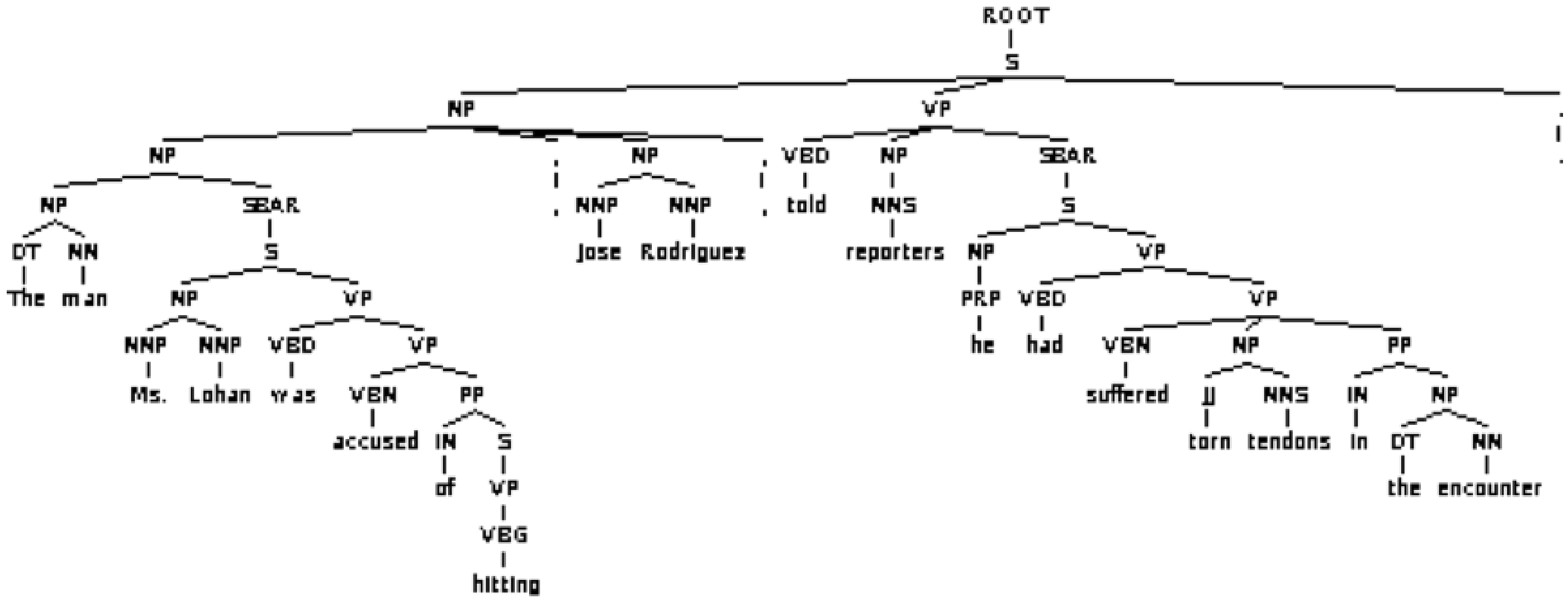
- Berkeley parser
  - *The man Ms. Lohan was accused of hitting, Jose Rodriguez, told reporters he had suffered torn tendons in the encounter.*

Demo



```
(ROOT
  (S
    (NP
      (NP
        (NP (DT The) (NN man))
        (SBAR
          (S
            (NP (NNP Ms.) (NNP Lohan))
            (VP (VBD was)
              (VP (VBN accused)
                (PP (IN of)
                  (S
                    (VP (VBG hitting)))))))))
      (, ,)
      (NP (NNP Jose) (NNP Rodriguez))
      (, ,))
    (VP (VBD told)
      (NP (NNS reporters))
      (SBAR
        (S
          (NP (PRP he))
          (VP (VBD had)
            (VP (VBN suffered)
              (NP (JJ torn) (NNS tendons))
              (PP (IN in)
                (NP (DT the) (NN encounter))))))))
    (. .)))
```

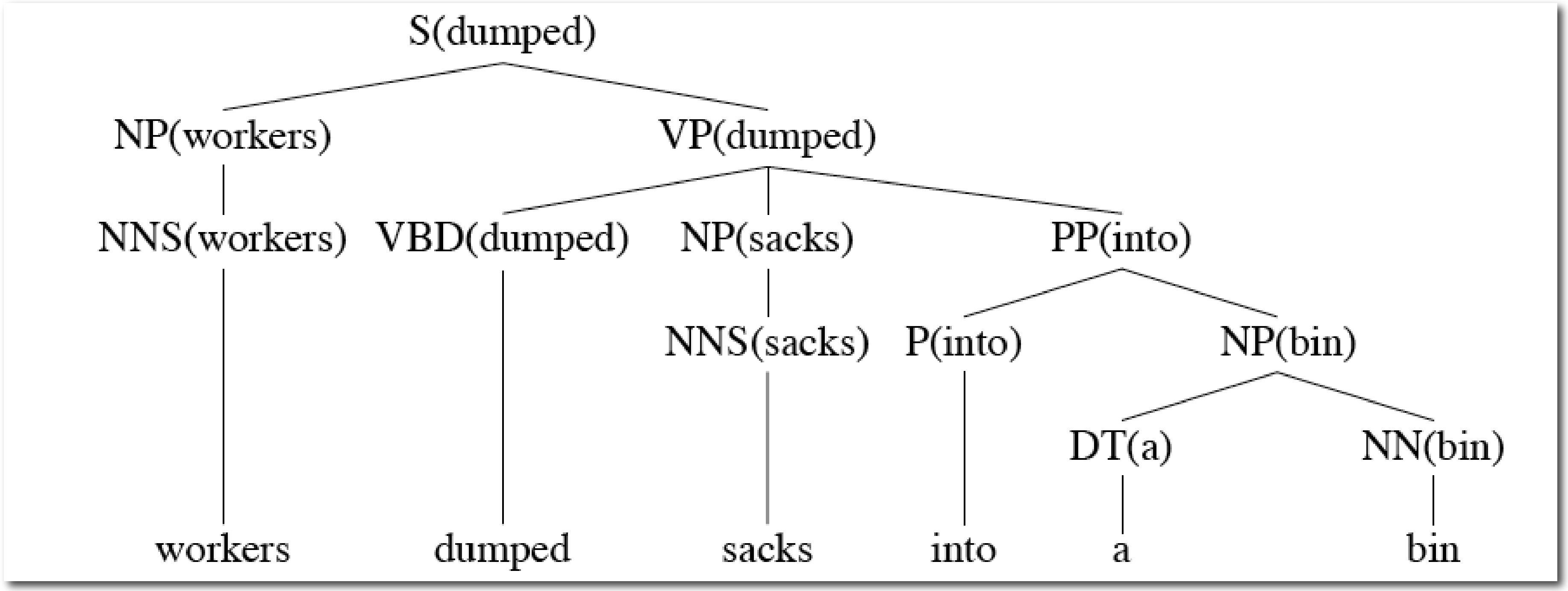
Demo


ROOT
S
NP
VP
NP
,
NP
,
VBD
NP
SBAR
.
NP
SBAR
NNP
NNP
told
NNS
S
DT
NN
S
Jose
Rodriguez
reporters
NP
VP
The
man
NP
VP
PRP
VBD
VP
NNP
NNP
VBD
VP
he
had
VBN
NP
PP
Ms.
Lohan
was
VBN
PP
suffered
JJ
NNS
IN
NP
accused
IN
S
torn
tendons
in
DT
NN
of
VP
the
encounter
VBG
hitting

Solution 2: Lexicalized Grammars

- Lexicalize the grammars with heads
- Compute the rule probabilities on these lexicalized rules
- Run probabilistic CKY as before

Dumped Example



How?

- We used to have
  - VP -> V NP PP   P(rule|VP)
    - That's the count of this rule divided by the number of VPs in a treebank
- Now we have fully lexicalized rules...
  - VP(dumped)-> V(dumped) NP(sacks)PP(into)

P(r|VP ^ dumped is the verb ^ sacks is the head of the NP ^ into is the head of the PP)

To get the counts for that..

Use Independence

- When stuck, exploit independence and collect the statistics you can…
- There are a large number of ways to do this...
- Let’s consider one generative story: given a rule we’ll
  1. Generate the head
  2. Generate the stuff to the left of the head
  3. Generate the stuff to the right of the head

Example

- So the probability of a lexicalized rule such as
  - VP(dumped) $\rightarrow$ V(dumped)NP(sacks)PP(into)
- Is the product of the probability of
  - *"dumped"* as the head of a VP
  - With nothing to its left
  - "*sacks*" as the head of the first right-side thing
  - "*into*" as the head of the next right-side element
  - And nothing after that

Example

- That is, the rule probability for

$$P(VP(dumped,VBD) \rightarrow VBD(dumped, VBD)\ NP(sacks,NNS)\ PP(into,P))$$

is estimated as

$$\begin{aligned} P_H(VBD|VP, dumped) & \times P_L(STOP|VP, VBD, dumped) \\ & \times P_R(NP(sacks,NNS)|VP, VBD, dumped) \\ & \times P_R(PP(into,P)|VP, VBD, dumped) \\ & \times P_R(STOP|VP, VBD, dumped) \end{aligned}$$

Framework

- That’s just one simple model
  - Collins Model 1
- You can imagine a gazzillion other assumptions that might lead to better models
- You just have to make sure that you can get the counts you need
- And that it can be used/exploited efficiently during decoding

Last Point

- Statistical parsers are getting quite good, but its still quite silly to expect them to come up with the correct parse given only syntactic information.
- But its not so crazy to think that they can come up with the right parse among the top-N parses.
- Lots of current work on
  - Re-ranking to make the top-N list even better
- What’s the problem with this argument?

Evaluation

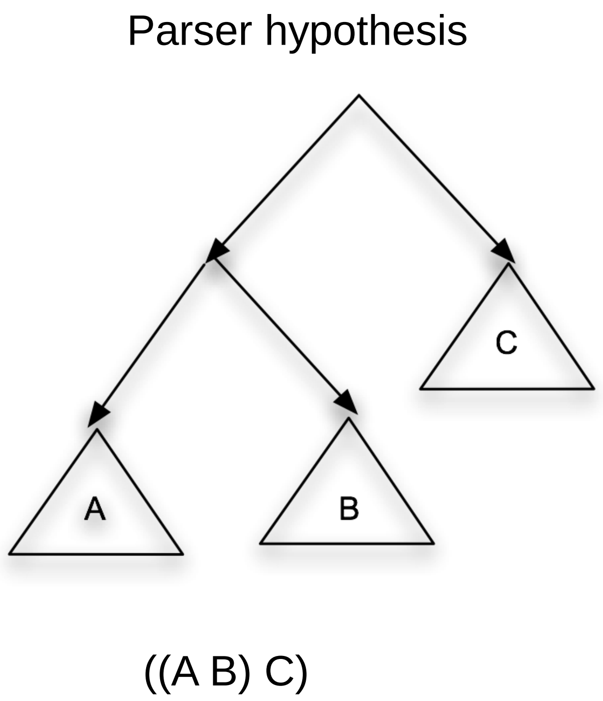
- So if it’s unreasonable to expect these probabilistic parsers to get the right answer what can we expect from them and how do we measure it.
- Look at the content of the trees rather than the entire trees.
  - Assuming that we have gold standard trees for test sentences

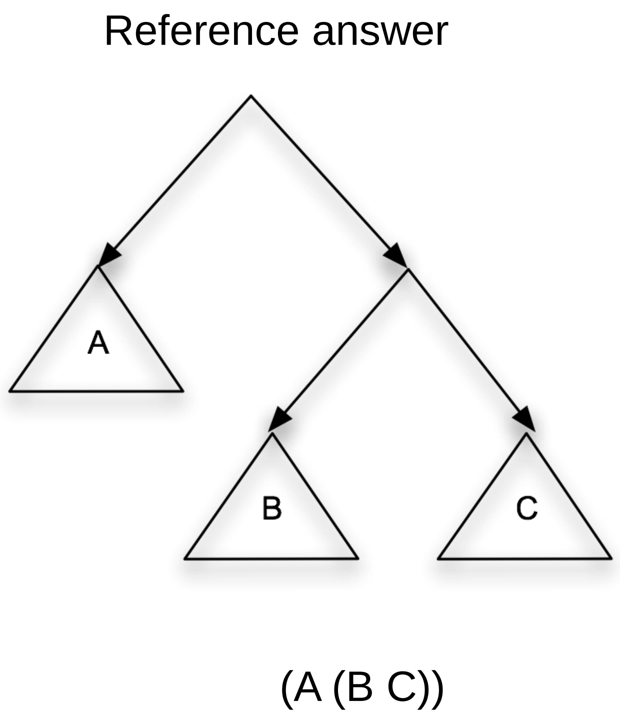
Evaluation

- Precision
  - What fraction of the sub-trees in our parse match corresponding sub-trees in the reference answer
    - How much of what we're producing is right?
- Recall
  - What fraction of the sub-trees in the reference answer did we actually get?
    - How much of what we should have gotten did we get?

Evaluation

- Crossing brackets





Finally

- In case someone hasn't pointed this out yet, the lexicalization stuff is a thinly veiled attempt to incorporate semantics into the syntactic parsing process…
  - Duhh..,. Picking the right parse requires the use of semantics.
  - Which we'll get to real soon now.