ĐẠI HỌC BÁCH KHOA HÀ NỘI
VIỆN CÔNG NGHỆ THÔNG TIN VÀ TRUYỀN THÔNG

5.2.Probabilistic parsing

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Motivation: how to choose a parse structure?

- Choice among parses, e.g.

  I saw a man with a telescope.

- As #rules increases, possibility of ambiguity goes *up*
- Large NYU grammars: Apple pie parser: 20,000-30,000 CF rules for English
- Choice between two rules: V DT NN PP

  (1) VP $\rightarrow$ V NP PP

  NP $\rightarrow$ DT NN

  (2) VP $\rightarrow$ V NP

  NP $\rightarrow$ DT NN PP

Word associations (bigrams pr)

Example:

Eat ice-cream (high freq)

Eat John (low, except on Survivor)

Some disadvantages:

- P(John decided to bake a) has a high probability
- Consider:
  $P(w_3) = P(w_3|w_2w_1)=P(w_3|w_2)P(w_2|w_1)P(w_1)$

The assumption is too strong, e.g., the subject of a sentence can 'select' the object:

Clinton admires honesty

➢ use syntactic structure to stop selection from propagating

- Consider Fred watered his mother's small garden. What is pr contributed from *garden*?
  - Pr(*garden*|*mother's small*) is not high ⇒ trigram model would *not* do well
  - Pr(*garden* | X is head of object NP *to water*) is higher

➢ use bigram + syntactic relation

Syntactic associations (Pr cfg)

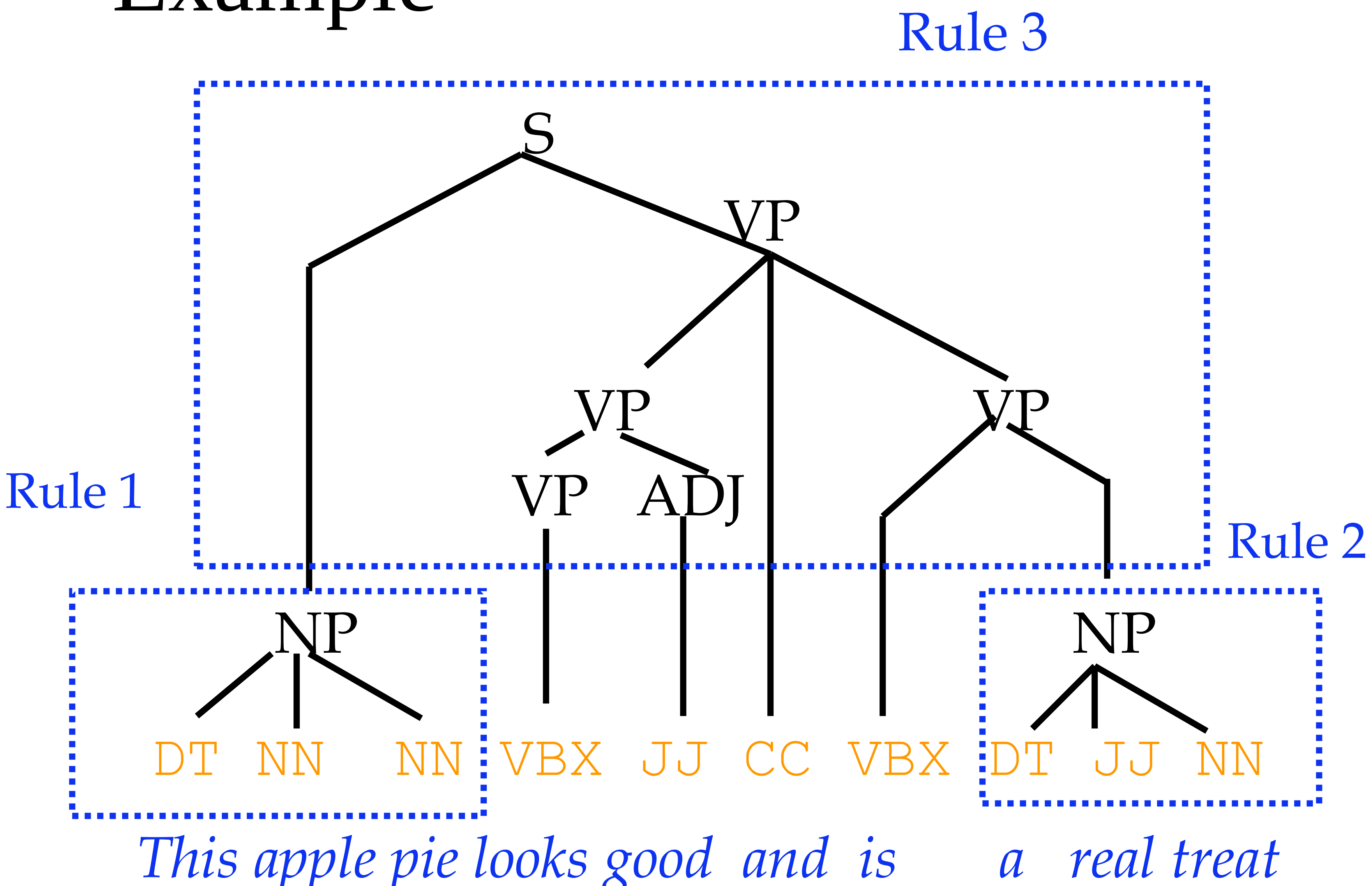
- V takes a certain kind of argument
  $\Rightarrow$ Verb-with-obj, verb-without-obj
- The correspondance between sbj and obj:
  John admires honesty
  Honesty admires John ???

Disadvantages:

- Grammar size increases
- 1 year of Wall Street Journal (WSJ corpus): 47,219 sentences, avg. length 23 words; bracketed by hand: only 4.7% or 2,232 have exactly *same* structure as any other in the corpus

➢ Can't do it all by table lookup. Instead, build up set of particular little pieces

Example



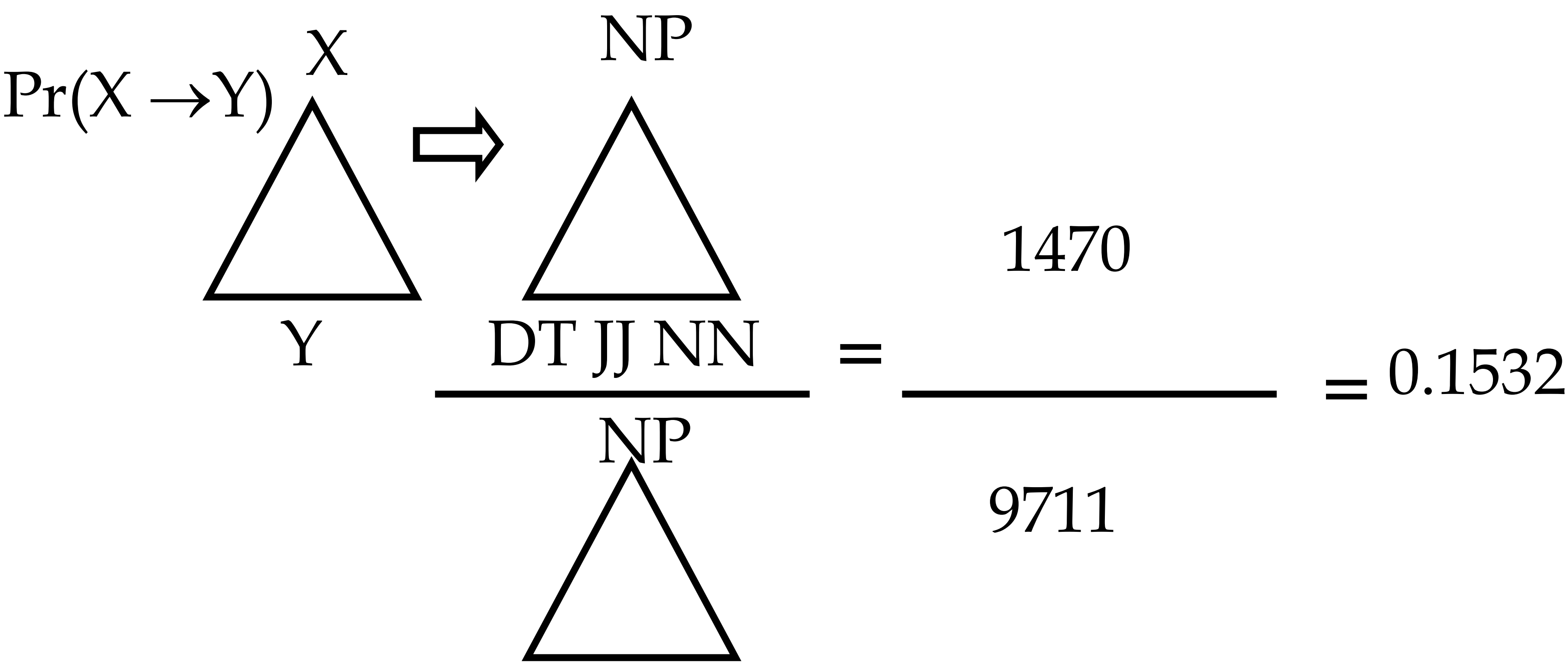
Rule 3
S
VP
VP
VP
VP
ADJ
Rule 1
Rule 2
NP
NP
DT NN NN VBX JJ CC VBX DT JJ NN
This apple pie looks good and is a real treat

Rules

1. NP→DT NN NN
2. NP→DT JJ NN
3. S→NP VBX JJ CC VBX NP

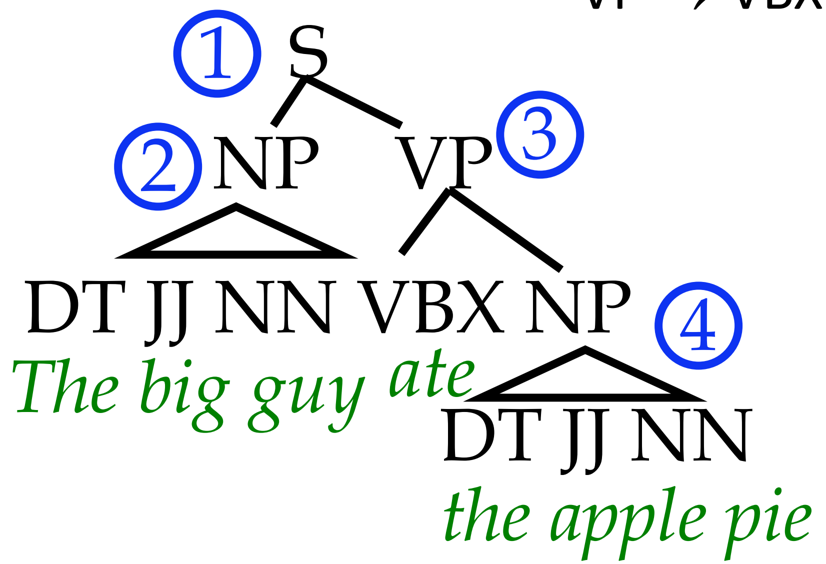
- Collapse (NNS, NN) to NX; (NNP, NNPs)=NPX; (VBP, VBZ, VBD)=VBX;
- Choose rules by their frequencies

Calculating frequencies



Pr calculation

$S \rightarrow NP\ VP$; 0.35
$NP \rightarrow DT\ JJ\ NN$; 0.1532
$VP \rightarrow VBX\ NP$; 0.302



Rule applied	*Pr chain*
1 $S \rightarrow NP\ VP$	0.35
2 $NP \rightarrow DT\ JJ\ NN$	0.1532 x 0.35 = 0.0536
3 $VP \rightarrow VBX\ NP$	0.302 x 0.0536= 0.0162
4 $NP \rightarrow DT\ JJ\ NN$	0.1532 x 0.0162=0.0025

Pr = 0.0025

PCFGs

- A PCFG G consists of the usual parts of a CFG
- A set of terminals, $\{w^k\}$, $k = 1, \ldots, V$
- A set of nonterminals, $\{N^i\}$, $i = 1, \ldots, n$
- A designated start symbol, N^1
- A set of rules, $\{N^i \rightarrow \zeta^j\}$, (where ζ^j is a sequence of terminals and nonterminals)

and

- A corresponding set of probabilities on rules such that:

$$\forall i \sum_j P(N^i \rightarrow \zeta^j) = 1$$

- Probability of a derivation (i.e. parse) tree:

$$P(T) = \prod_{i=1..n} p(r(i))$$

Assumptions

- ***Place Invariance:*** The probability of a subtree does not depend on *where in the string* the words it dominates are.

  $\forall k$, $P(N_{jk}(k+c) \rightarrow \zeta)$ is the same

- ***Context Free:*** The probability of a subtree does not depend on words *not dominated* by the subtree.

  $P(N_{jkl} \rightarrow \zeta |$ anything outside k through $l) = P(N_{jkl} \rightarrow \zeta)$

- ***Ancestor Free:*** The probability of a subtree does not depend on nodes in the derivation *outside* the subtree

  $P(N_{jkl} \rightarrow \zeta |$ anything ancestor nodes outside $N_{jkl}) = P(N_{jkl} \rightarrow \zeta)$

Parsing algorithms

- CKY
- Beam search
- Agenda/chart-based search
- …

CKY with probabilities

- Data structure:
  - Dynamic programming array $\pi[i,j,a]$ holds the maximum probability for a constituent with nonterminal a spanning words $i \ldots j$.
  - Backptrs store links to constituents in tree
- Output: Maximum probability of parse

Compute Pr by induction

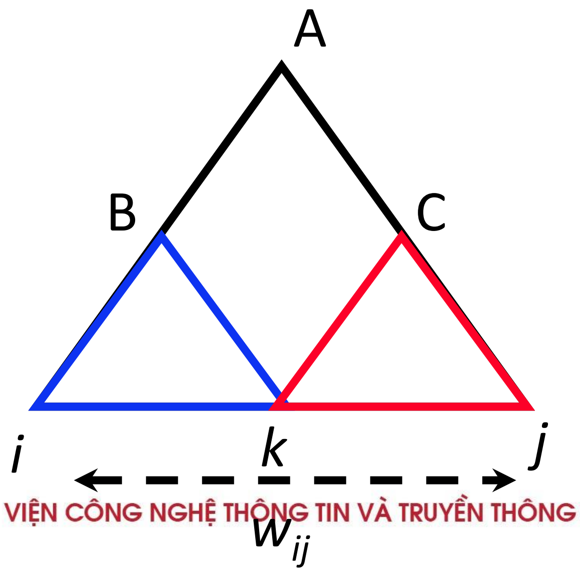
- Base case: input is a single word.

  $\Pr(\text{tree}) = \text{pr}(A \rightarrow w_i)$

- Recursive case. Input is a string of words.

$A \overset{*}{\Rightarrow} w_{ij}$ if $\exists k$: $A \rightarrow BC$, $B \overset{*}{\Rightarrow} w_{ik}$, $C \overset{*}{\Rightarrow} w_{kj}$, $i \le k \le j$.

$p[i,j] = \max(p(A \rightarrow BC) \times p[i,k] \times p[k,j])$.



function CYK(*words,grammar*) **returns** *best_parse*

Create and clear *p*[*num_words*,*num_words*,*num_nonterminals*]

```
# base case
for i = 1 to num_words
    for A = 1 to num_nonterminals
        if A → w_i is in grammar then
            π[i, i, A] = P(A → w_i)

# recursive case
for j = 2 to num_words
    for i = 1 to num_words-j+1
        for k = 1 to j-1
            for A = 1 to num_nonterminals
            for B = 1 to num_nonterminals
            for C = 1 to num_nonterminals
                prob = π[i, k, B] × p[i+k, j-k, C] × P(A→BC)
                if (prob > π[i, j, A]) then
                    π[i, j, A] = prob
                    B[i, j, A] = {k, A, B}
```

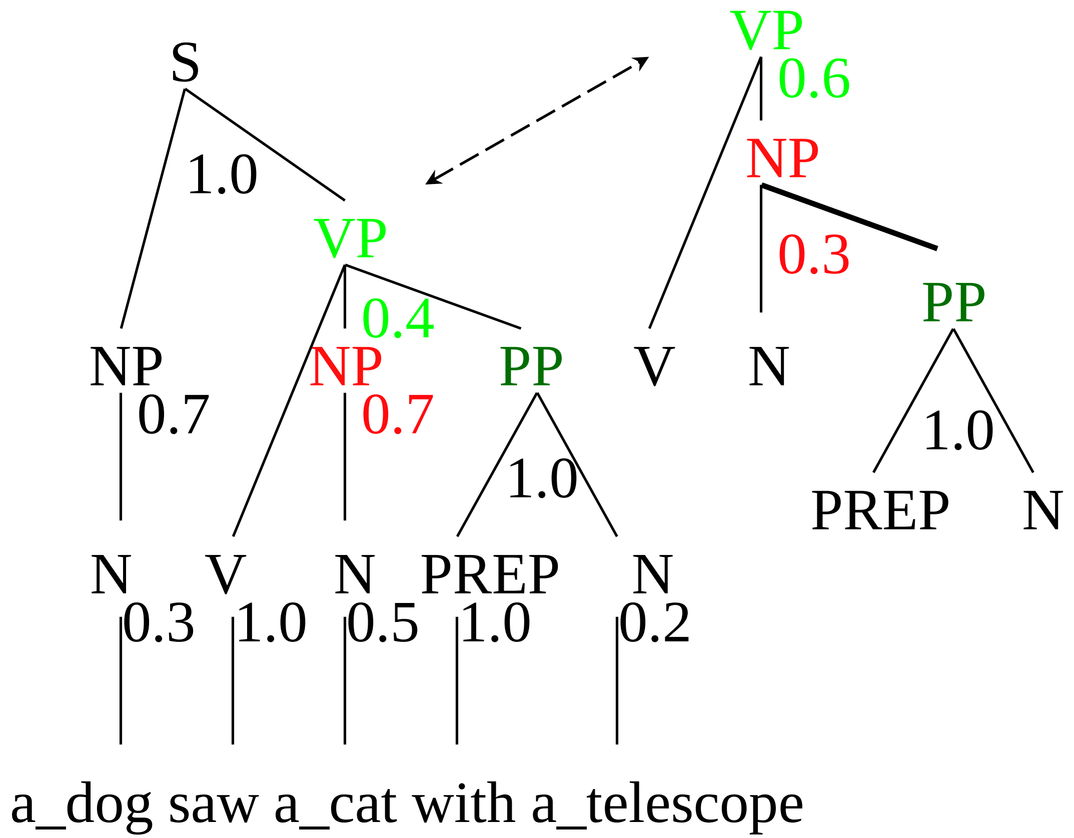
Calculation of Viterbi probabilities (CKY algorithm)

$S \rightarrow NP\ VP$	1.0	$NP \rightarrow NP\ PP$	0.4
$PP \rightarrow P\ NP$	1.0	$NP \rightarrow$ *astronomers*	0.1
$VP \rightarrow V\ NP$	0.7	$NP \rightarrow$ *ears*	0.18
$VP \rightarrow VP\ PP$	0.3	$NP \rightarrow$ *saw*	0.04
$P \rightarrow$ *with*	1.0	$NP \rightarrow$ *stars*	0.18
$V \rightarrow$ *saw*	1.0	$NP \rightarrow$ *telescopes*	0.1

	1	2	3	4	5
1	$\delta_{NP} =$ 0.1		$\delta_S =$ 0.0126 0.0504		$\delta_S =$ 0.0009072
2		$\delta_{NP} =$ 0.04 $\delta_V =$ 1.0	$\delta_{VP} =$ 0.126		$\delta_{VP} =$ 0.009072
3			$\delta_{NP} =$ 0.18		$\delta_{NP} =$ 0.01296
4				$\delta_P =$ 1.0	$\delta_{PP} =$ 0.18
5					$\delta_{NP} =$ 0.18
	astronomers	*saw*	*stars*	*with*	*ears*

Pr calculation

1. S → NP VP 1.0
2. VP → V NP PP 0.4
3. VP → V NP 0.6
4. NP → N 0.7
5. NP → N PP 0.3
6. PP → PREP N 1.0
7. N → a_dog 0.3
8. N → a_cat 0.5
9. N → a_telescop 0.2
10. V → saw 1.0
11. PREP → with 1.0



$P_l = 1\times.7\times.4\times.3\times.7\times1\times.5\times1\times1\times.2 = .00588$

$P_r = 1\times.7\times.6\times.3\times.3\times1\times.5\times1\times1\times.2 = .00378$

- P_l is chosen

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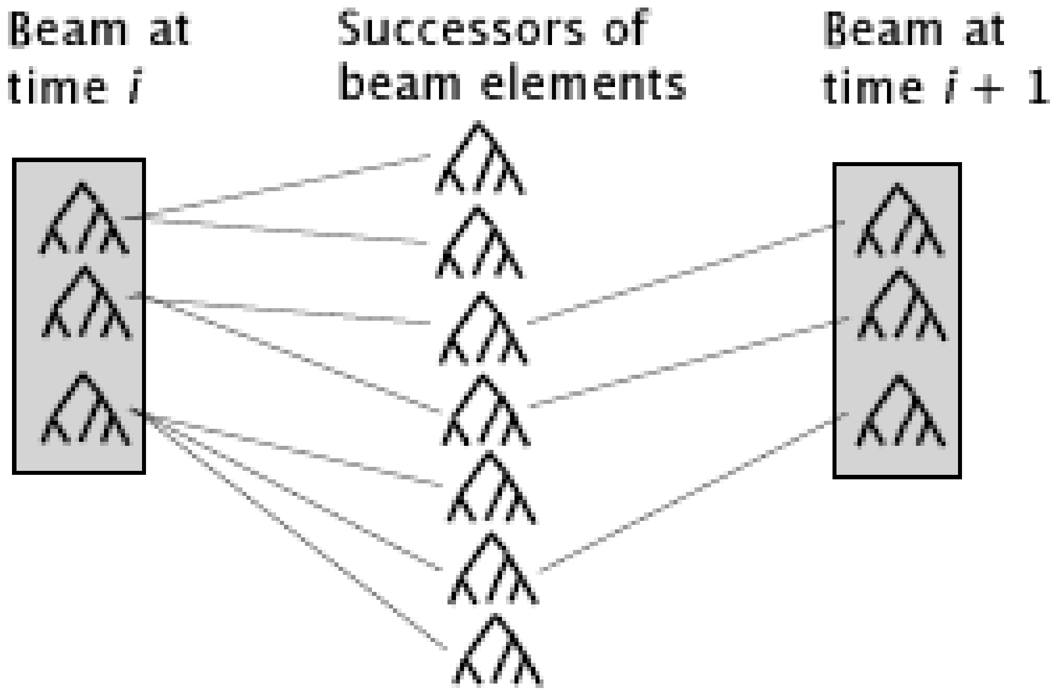
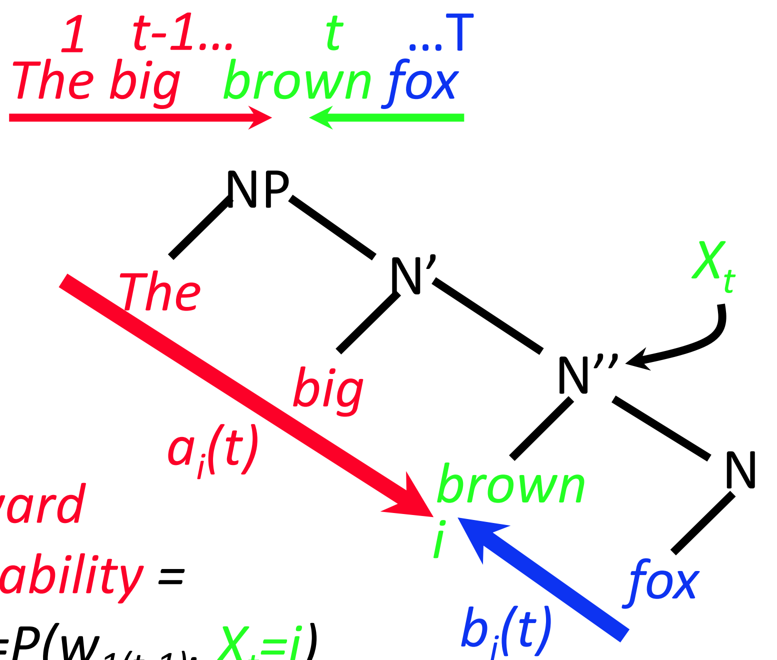
Beam search

- State space search
- States are partial parses with an associated probability
  - Keep only the top scoring elements at each stage of the beam search
- All parses of a sentence have the same number N steps



Forward and Backward Pr

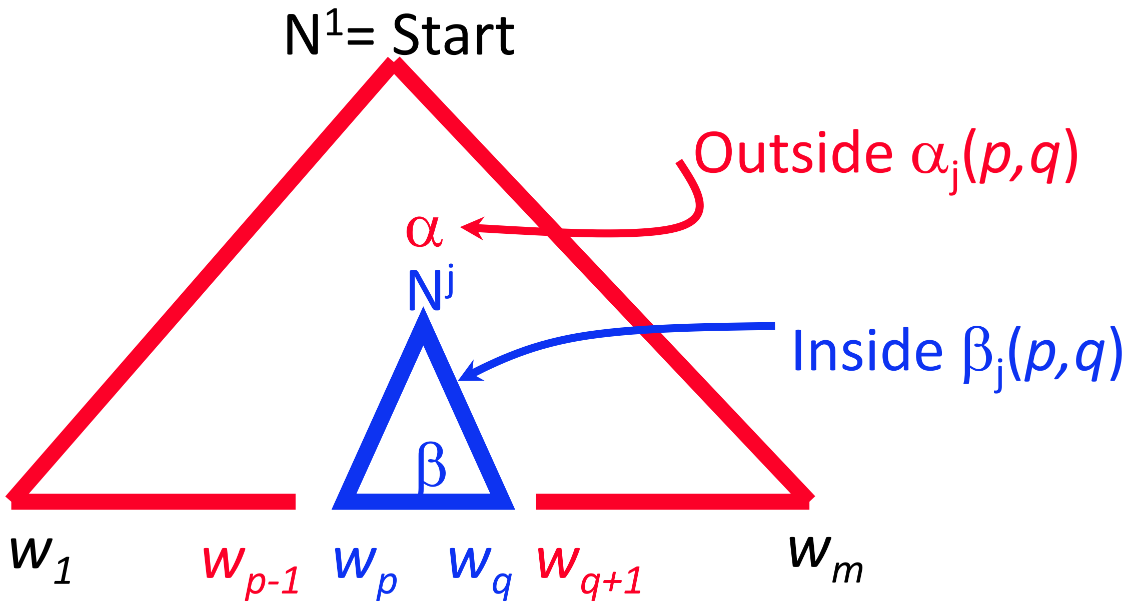


Forward Probability =
$a_i(t)=P(w_{1(t-1)}, X_t=i)$

Backward Probability =
$b_i(t)=P(w_{tT} \mid X_t=i)$

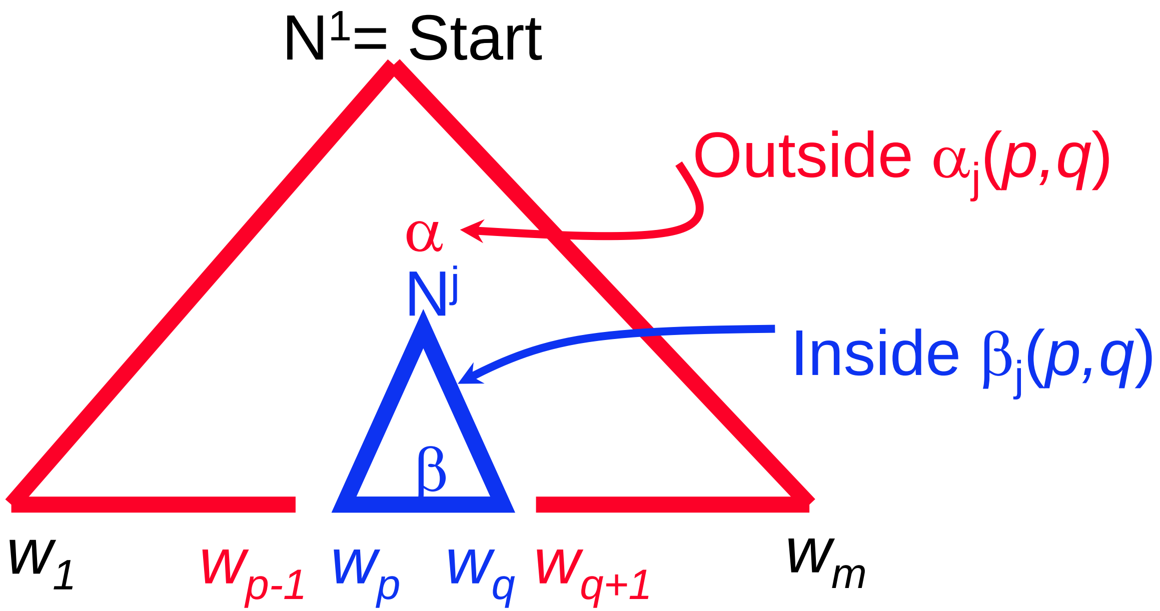
- *Forward*=probability of everything <u>*above & including*</u> a certain node
- *Backward*= probability of of everything *below* the node, *given* the node

Inside and outside probabilities



- N_{pq} = Nonterminal N^j spans positions p through q in string (phrase N^j dominates words w_{pq})
- α_j = outside probabilities
- β_j = inside probabilities
- N^j *dominates* words w_p … w_q, *iff* $N^j \Rightarrow^* w_p \ldots w_q$

Inside and outside probabilities



$\alpha_j(p,q)=P(w_{1(p-1)}\ ,\ N_{pq}^j, w_{(q+1)m}|G)$

$\beta_j(p,q)=P(w_{pq}|N_{pq}^j, G)$

$$\alpha_j(p,q)\ \beta_j(p,q) = P(N^1 \Rightarrow * \ w_{1m}\ ,\ N^j \Rightarrow * \ w_{pq}\ |\ G)$$
$$= \ P(N^1 \Rightarrow * \ w_{1m}\ |G) \bullet P(N^j \Rightarrow * \ w_{pq}\ |\ N^1 \Rightarrow * \ w_{1m},\ G)$$

Compute Pr of a string

- We use the ***Inside Algorithm***, a dynamic programming algorithm based on the inside probabilities:

$P(w_{1m}|G) = P(N^1 \Rightarrow^* w_{1m}|G) = P(w_{1m}|N_{1m}^1, G) = \beta_1(1,m)$

- Base Case:

$$\beta_j(k,k) = P(w_k|N_{kk}^j, G) = P(N^j \rightarrow w_k|G)$$

- Induction:

$$\beta_j(p,q) = \Sigma_{r,s}\Sigma_{d\in(p,q-1)} P(N^j \rightarrow N^r N^s)\, \beta_r(p,d)\, \beta_s(d+1,q)$$

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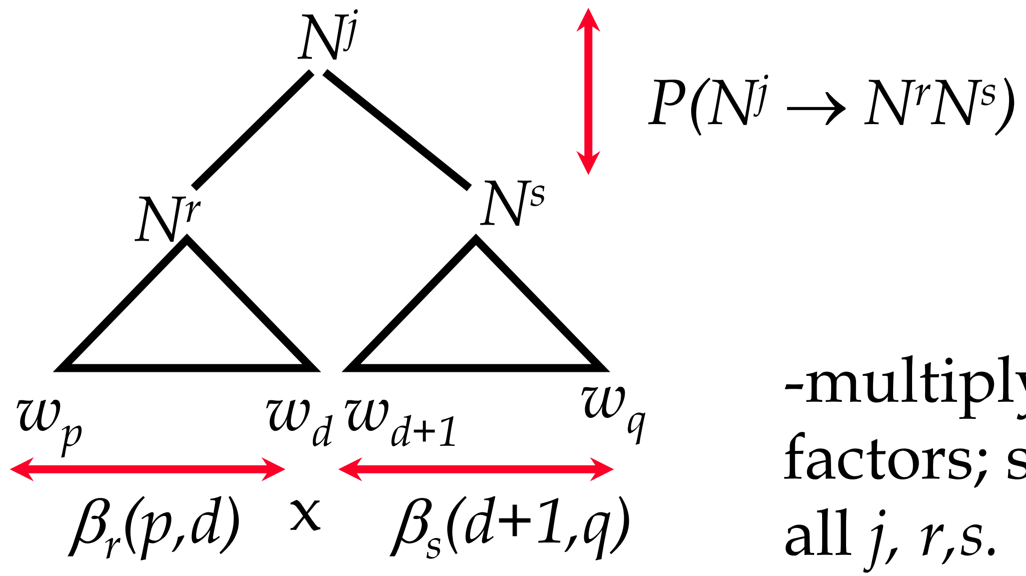
Induction

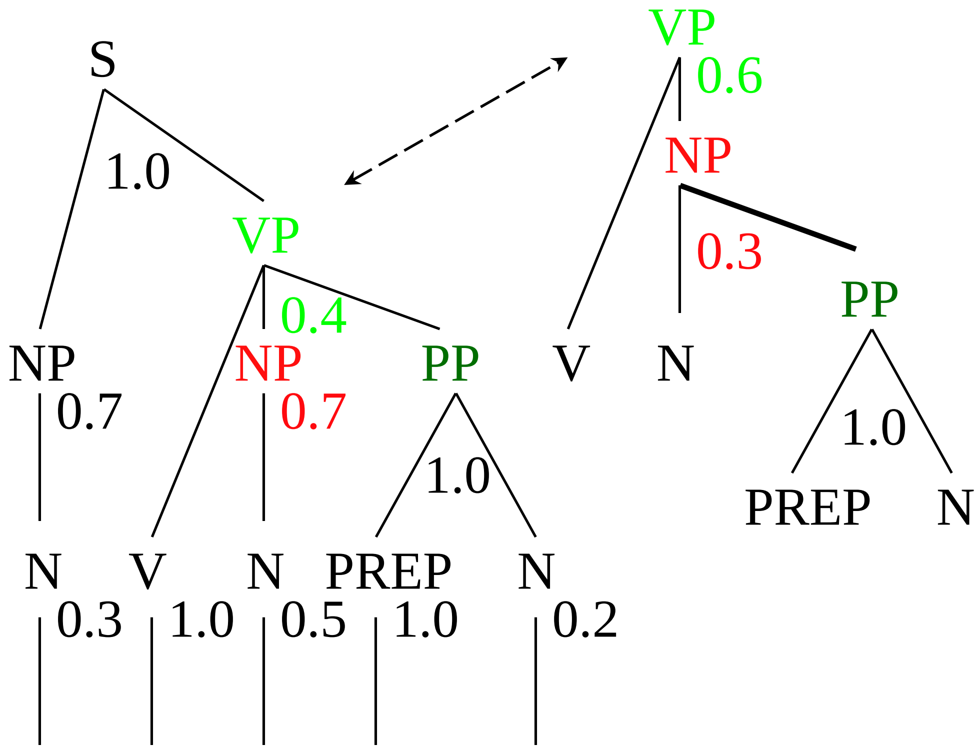
Find $\beta_j(p,q)$ for p < q – calculate over all ‘splits’ j – do this ‘bottom up’



-multiply these 3 factors; sum over all *j, r,s.*

Example PCFG

1. S → NP VP 1.0
2. VP → V NP PP 0.4
3. VP → V NP 0.6
4. NP → N 0.7
5. NP → N PP 0.3
6. PP → PREP N 1.0
7. N → a_dog 0.3
8. N → a_cat 0.5
9. N → a_telescope 0.2
10. V → saw 1.0
11. PREP → with 1.0

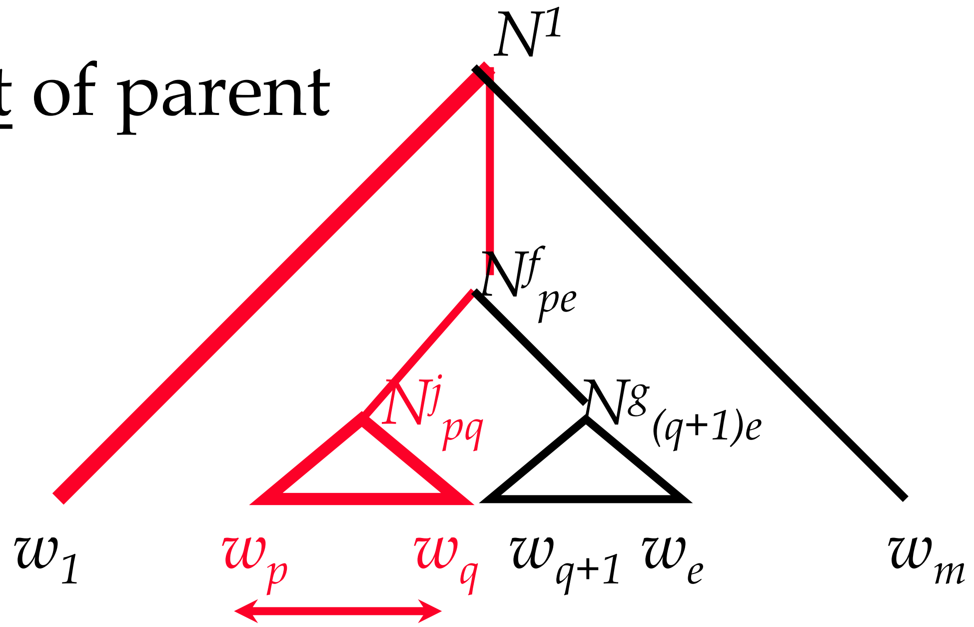


P(a_dog saw a_cat with a_telescope) =

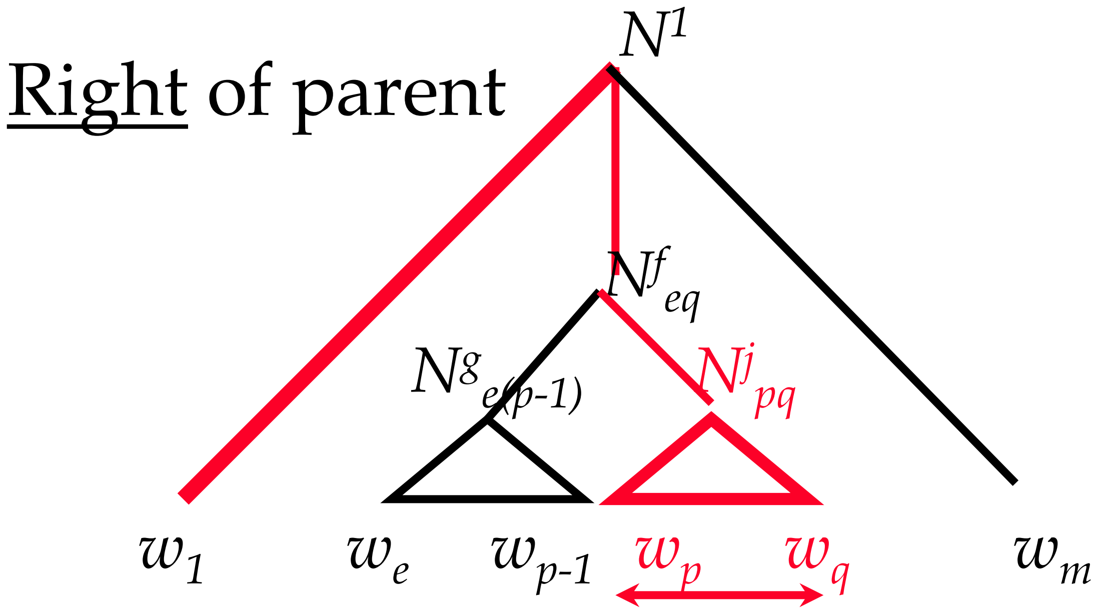
1×.7×.4×.3×.7×1×.5×1×1×.2 + ... ×.6... ×.3... = .00588 + .00378 = .00966

Compute outside Pr, $\alpha_j(p,q)$

<u>Left</u> of parent



Compute outside Pr, $\alpha_j(p,q)$

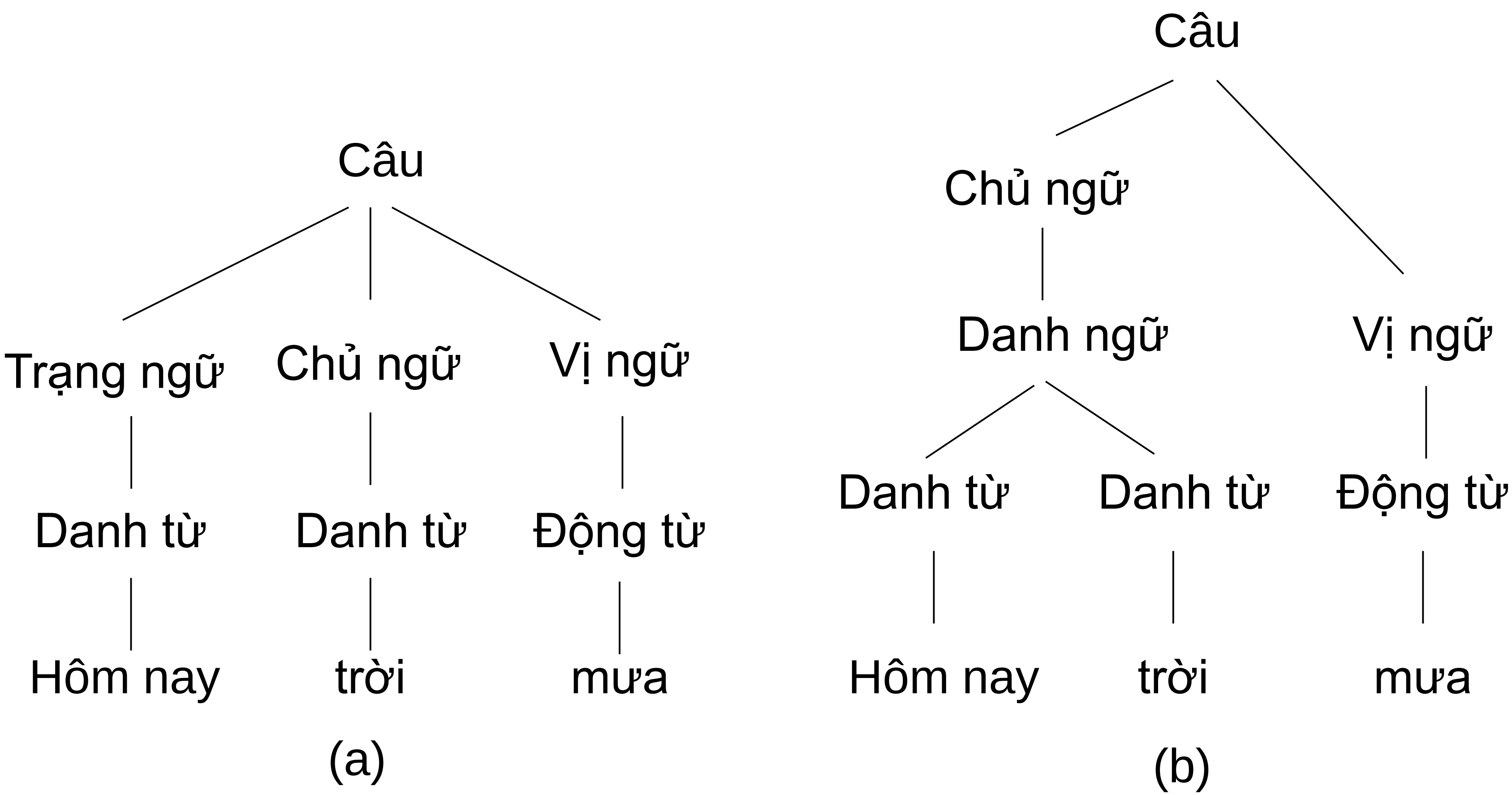


Sum over both; restrict $g \neq j$
to avoid double counting $N^j N^j$

Ambiguity in Vietnamese syntactic parsing

- 2 types of ambiguities:
  - A sentence can be understood by different ways, resulting in different syntactic trees
    - Eg., "*Tôi nhìn thấy anh Hải ở tầng hai*"
  - A sentence with only one meaning but the syntactic parser generates more than one syntactic tree, in which only one tree is correct.
    - Eg., "*Hôm nay trời mưa*"

Ambiguity in Vietnamese syntactic parsing



Ambiguity in Vietnamese syntactic parsing

Solution:

Solution 1: Using more detailed syntactic labels Phân loại chi tiết hơn các nhãn từ loại/ngữ loại:

Instead of the rule

<Danh ngữ> $\rightarrow$ <Danh từ><Danh từ>

Using a rule:

<Danh ngữ> $\rightarrow$ <Danh từ loại A><Danh từ loại B>.

Disadvantages:

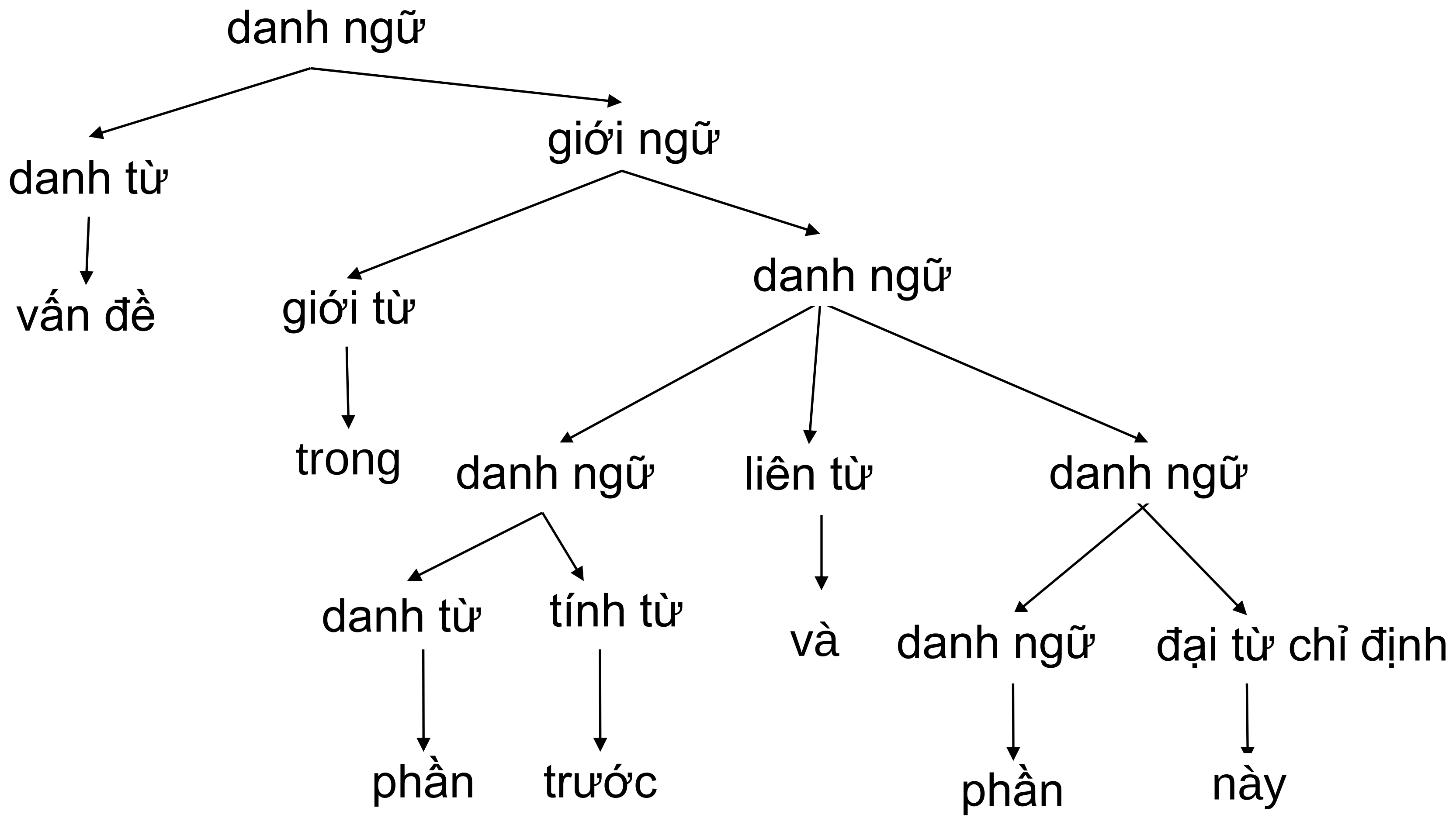
- The set of syntactic labels is not unique.
- The size of the rule set is increased remarkable
- The rule set needs to be created manually → difficult to be done

Ambiguity in Vietnamese syntactic parsing

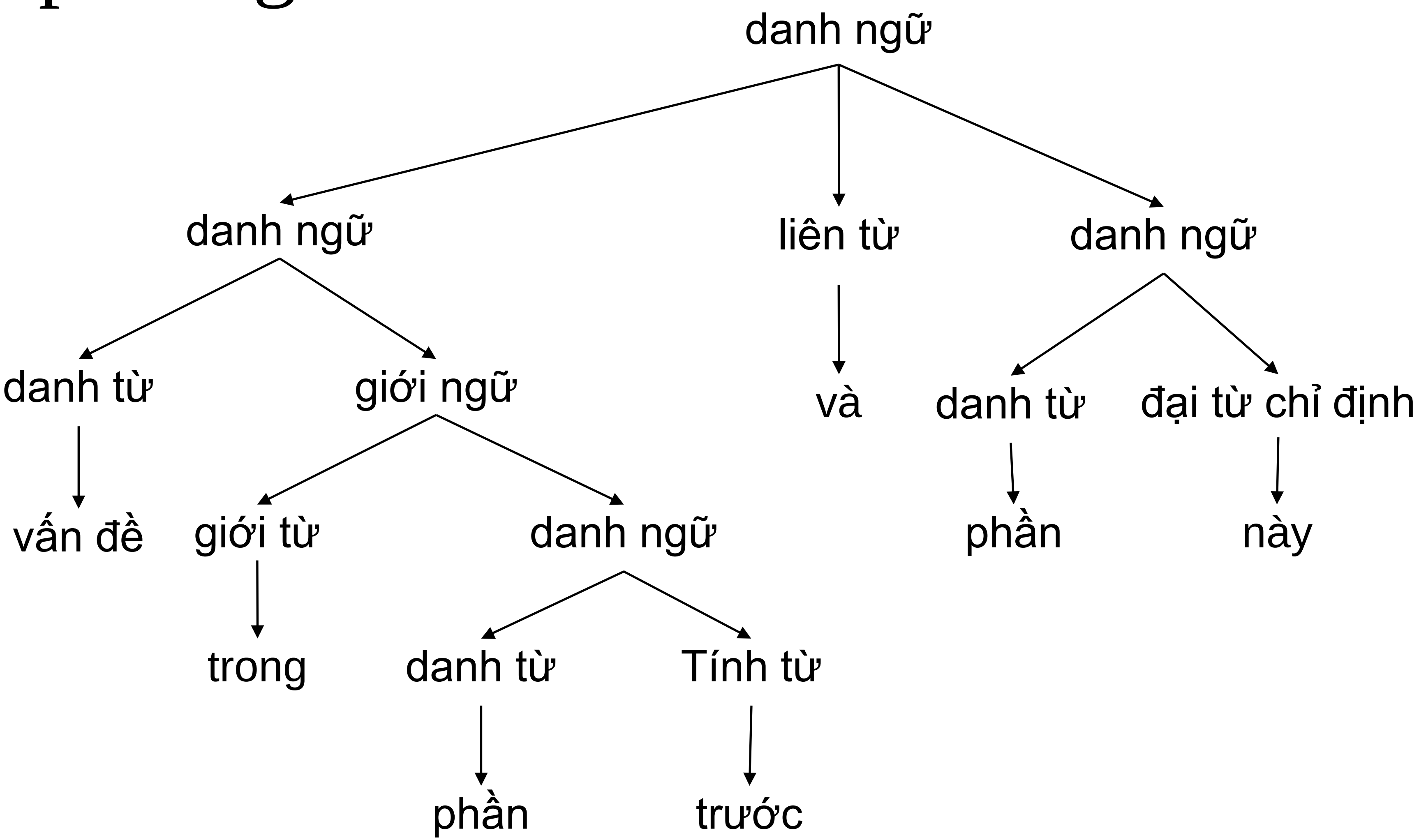
Solution 2: add probabilities into the rule set

- The ambiguity in the sentence "*Tôi nhìn thấy anh Hải ở tầng hai*" can be solved
- The ambiguity of word characteristics has not been solved.
- Eg., noun phrase "*vấn đề trong phần trước và phần này*"

Ambiguity in Vietnamese syntactic parsing



Ambiguity in Vietnamese syntactic parsing



Specific words may affect the result of syntactic parsing

For example:

- "*Tôi ăn*" rarely be accepted as a sentence because the information in that sentence is small.
- "*Tôi đang ăn*" is more likely to be accepted.

➢ Has to consider the characteristic of the main word in a sentence

2. Ambiguity due to removing the conjunction word
   - Can say: *bạn tôi, con tôi;*
   - Cannot say: *con chó tôi, con mèo tôi*.

➢ Word also play an important role in syntactic parsing

➢ Add word information to the grammar (enriching PCFG)

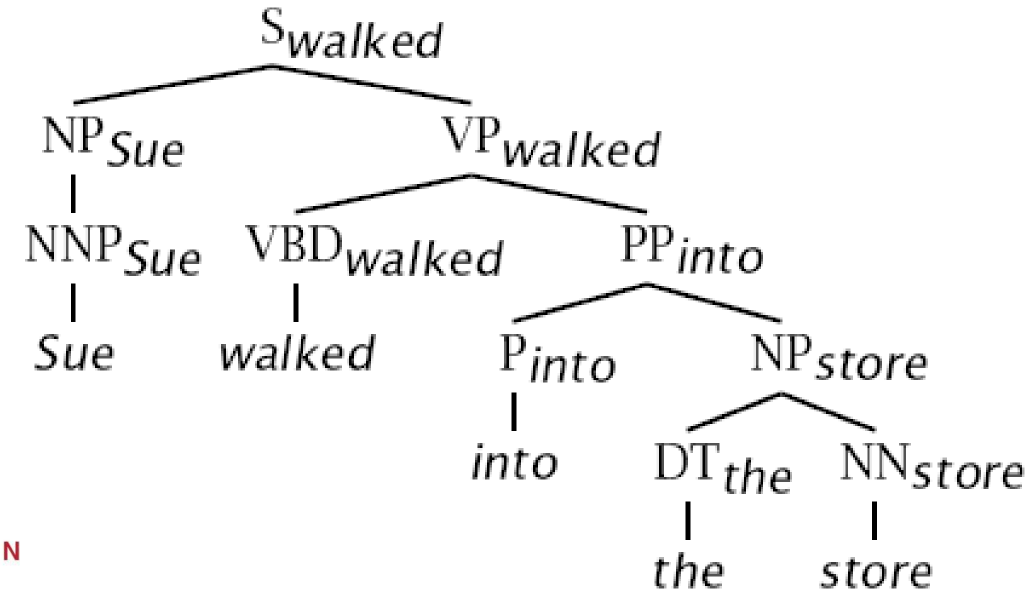
Enriching a PCFG

- A naive PCFG works quite poorly due to the independence assumptions
- Fix: encode more information into the nonterminal space
  - Structure sensitivity
    - Expansion of nodes depends a lot on their position in the tree (independent of lexical content)
    - E.g., enrich nodes by also recording their parents: ${}^{S}NP$ is different to ${}^{VP}NP$

Enriching a PCFG

- (Head) Lexicalization (Collins 1997; Charniak 1997)
  - The head word of a phrase gives a good representation of the phrase's structure and meaning
  - Puts the properties of words back into a PCFG

VP(dumped) → VBD(dumped) NP(sacks) PP(into) $3*10^{-10}$
VP(dumped) → VBD(dumped) NP(cats) PP(into) $8*10^{-11}$



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Enriching a PCFG

- Lexicalizated PCFG : PLCFG (Probabilistic Lexicalized CFG, Collins 1997; Charniak 1997)
- Puts the properties of words back into a PCFG
- Head structure
  - Each node in the parsed tree is attached with a *lexical head*
  - To define a *head* node, we have to find it among all of its children (define *head* in the RHS of a rule).

Enriching a PCFG

$VP(dumped) \rightarrow VBD(dumped)\ NP(sacks)\ PP(into)\ 3*10^{-10}$

$VP(dumped) \rightarrow VBD(dumped)\ NP(cats)\ PP(into)\ 8*10^{-11}$

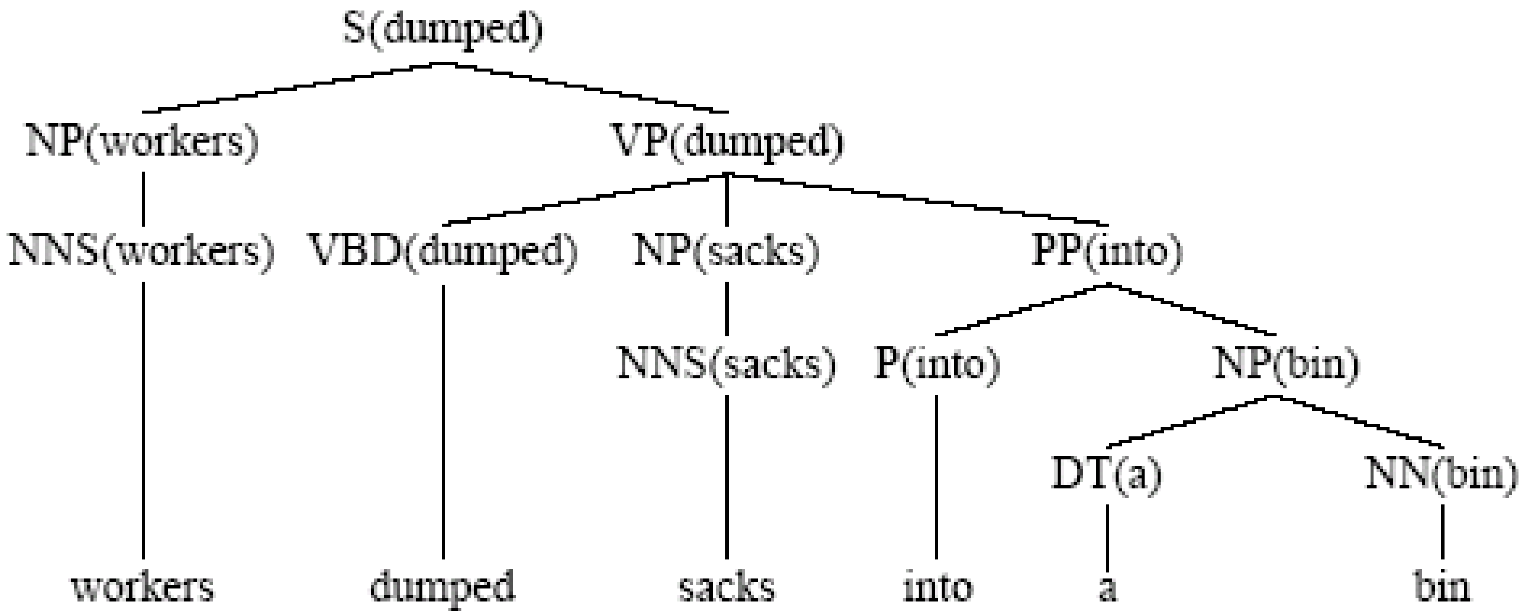

Figure 12.12 A lexicalized tree from Collins (1999).

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Limitations of PLCFG

VP -> VBD NP PP

VP(*dumped*) -> VBD(*dumped*) NP(*sacks*) PP(*into*)

- We don't have a large enough corpus!
  - To represent all syntactic cases for each word

Penn Treebank

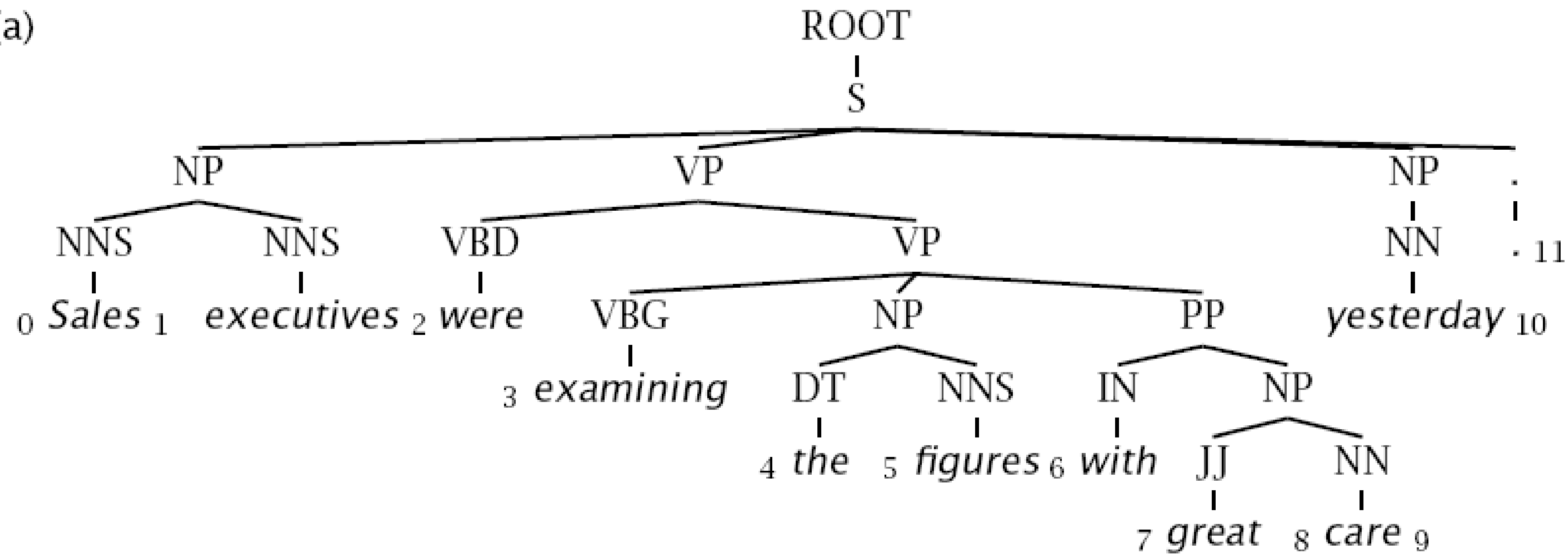
- The Penn Treebank – 1 million words of parsed English WSJ – has been a key resource
- Sparseness:
  - 965,000 constituents, but only 66 WHADJP, of which only 6 aren't *how much* or *how many*
- Most intelligent processing depends on bilexical statistics: likelihoods of relationships between pairs of words.

A Penn Treebank tree

```
( (S
    (NP-SBJ
      (NP (NNP Pierre) (NNP Vinken) )
      (, ,)
      (ADJP
        (NP (CD 61) (NNS years) )
        (JJ old) )
      (, ,) )
    (VP (MD will)
      (VP (VB join)
        (NP (DT the) (NN board) )
        (PP-CLR (IN as)
          (NP (DT a) (JJ nonexecutive) (NN director) ))
        (NP-TMP (NNP Nov.) (CD 29) )))
    (. .) ))
```

Evaluation

(a)



(b) Brackets in gold standard tree (a.):
S-(0:11), **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), *NP-(9:10)

(c) Brackets in candidate parse:
S-(0:11), **NP-(0:2)**, VP-(2:10), VP-(3:10), NP-(4:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

(d)

Precision:	3/8 = 37.5%	Crossing Brackets:	0
Recall:	3/8 = 37.5%	Crossing Accuracy:	100%
Labeled Precision:	3/8 = 37.5%	Tagging Accuracy:	10/11 = 90.9%
Labeled Recall:	3/8 = 37.5%		

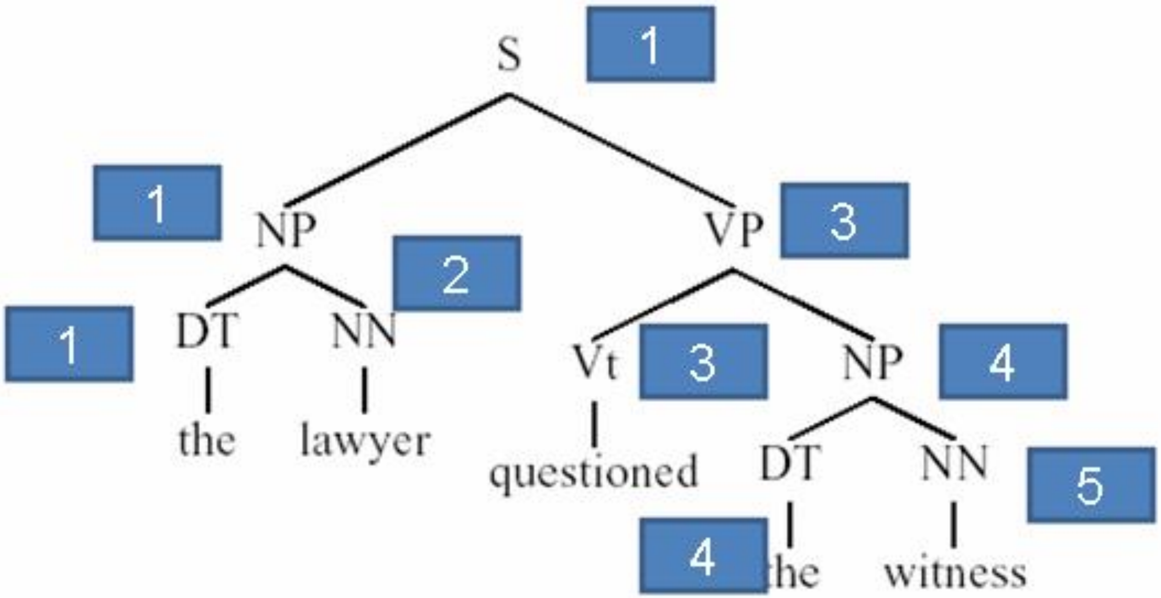
Performance's Measurements

		Human assignments		Total
		Yes	**No**	
System assignments	**Yes**	HSA	SA - HSA	SA
	No	HA - HSA		
Total		HA		

Precision: %assignments made that were correct (%THợp hệ tính đúng).
Recall: %possible assignments that were actually assigned (%THợp hệ tính đúng so với con người).

$$precision = \frac{HSA}{SA} \qquad recall = \frac{HSA}{HA}$$

Represent a tree by its syntactic constitutes



⇓

Label	Start Point	End Point
NP	1	2
NP	4	5
VP	3	5
S	1	5

Evaluate

Precision and Recall

Label	Start Point	End Point
NP	1	2
NP	4	5
NP	4	8
PP	6	8
NP	7	8
VP	3	8
S	1	8

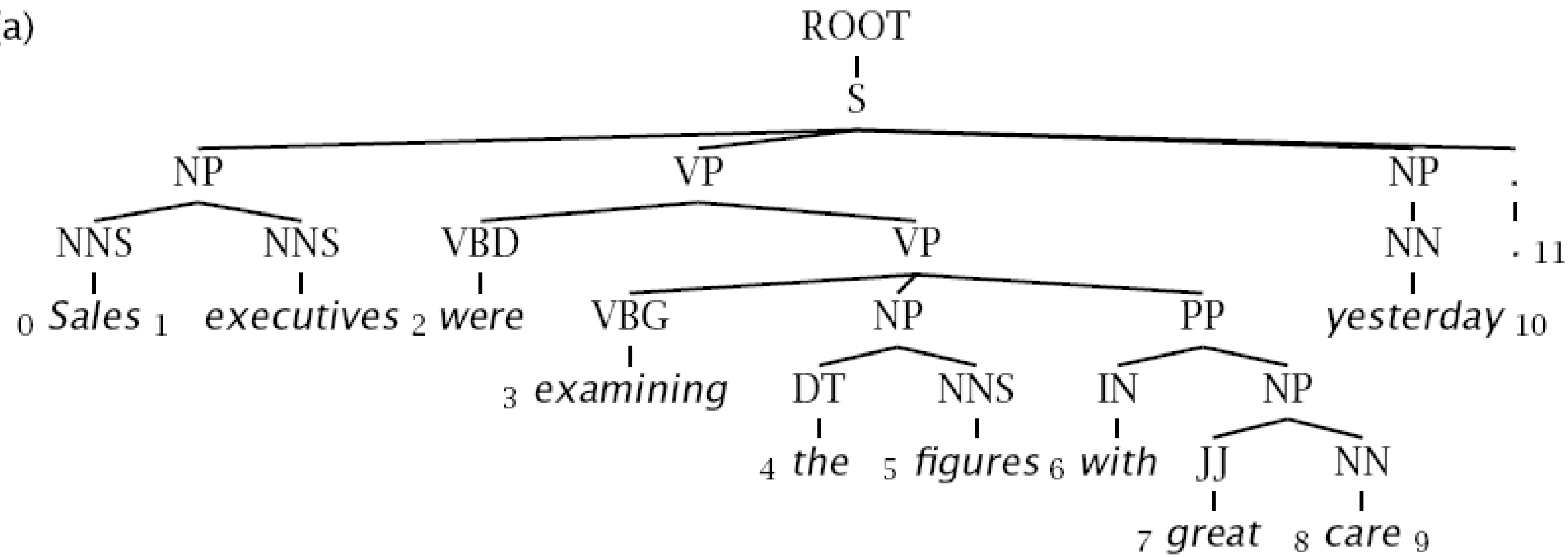
Label	Start Point	End Point
NP	1	2
NP	4	5
PP	6	8
NP	7	8
VP	3	8
S	1	8

- G = number of constituents in gold standard = 7
- P = number in parse output = 6
- C = number correct = 6

$$\text{Recall} = 100\% \times \frac{C}{G} = 100\% \times \frac{6}{7} \qquad \text{Precision} = 100\% \times \frac{C}{P} = 100\% \times \frac{6}{6}$$

Example 2

(a)



(b) Brackets in gold standard tree (a.):
S-(0:11), **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), *NP-(9:10)

(c) Brackets in candidate parse:
S-(0:11), **NP-(0:2)**, VP-(2:10), VP-(3:10), NP-(4:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

(d)

Precision:	3/8 = 37.5%	Crossing Brackets:	0
Recall:	3/8 = 37.5%	Crossing Accuracy:	100%
Labeled Precision:	3/8 = 37.5%	Tagging Accuracy:	10/11 = 90.9%
Labeled Recall:	3/8 = 37.5%		

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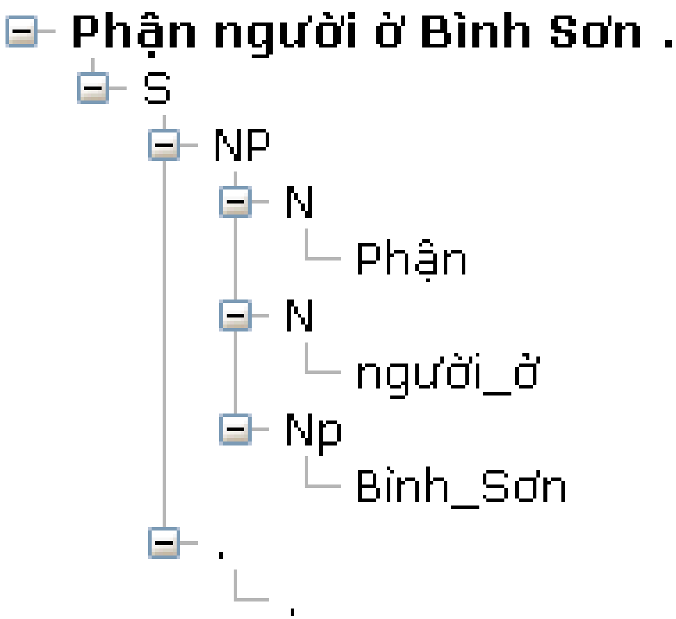
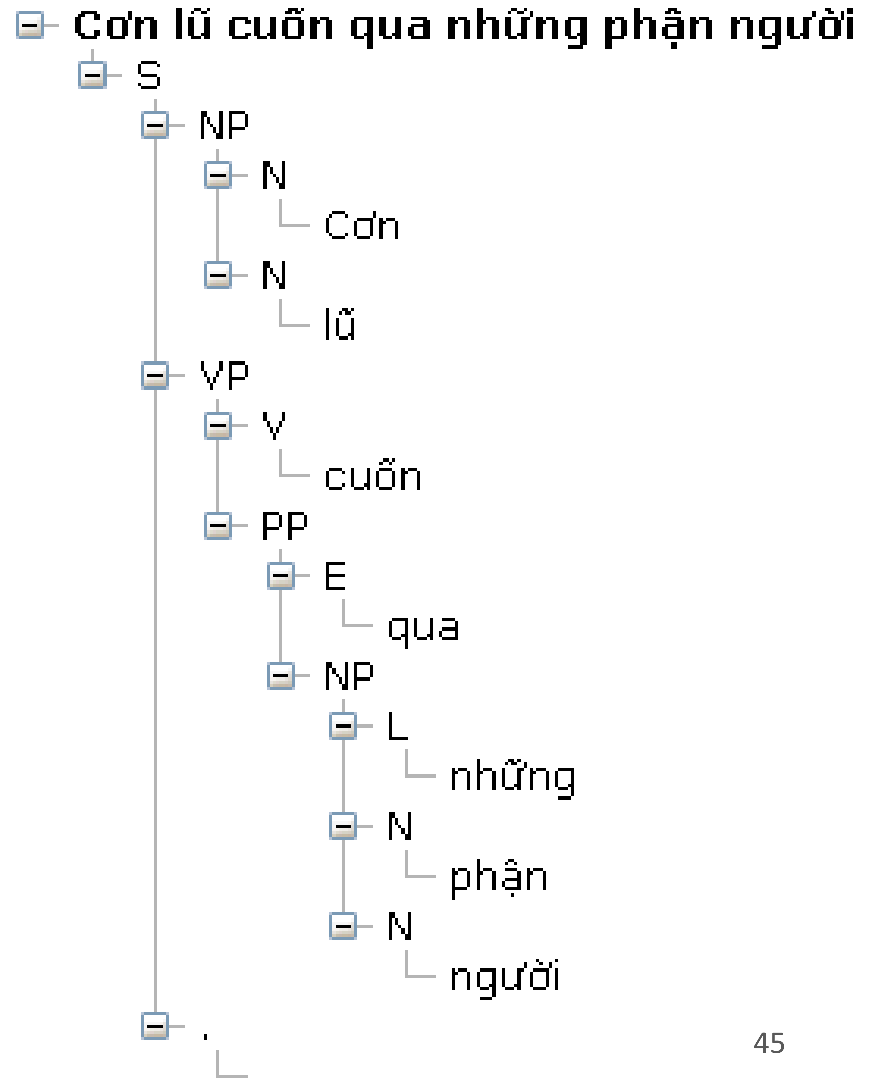
Exercise – compute P, R

Gold standard syntactic structure:

- (S (NP (N Cơn)(N lũ)) (VP(V cuốn)(V qua) (NP (L những)(N phận)(N người))) (. .))
- (S(NP(N Phận)(N người) (PP(E ở) (NP(Np Bình Sơn)))(. .))

Automatically generated syntactic structure:





Some syntactic parsers:

- CFG (context free grammar):
  - Berkeley : http://nlp.cs.berkeley.edu/software.shtml
  - Charniak: http://bllip.cs.brown.edu/resources.shtml
- HPSG (Head-driven Phrase Structure Grammar)
  - Enju, deepNLP: https://mynlp.github.io/enju/
- Depedency grammar
  - ClearNLP : http://clearnlp.wikispaces.com/depParser
  - Google SyntaxNet: open-source, using deep learning
  - https://research.googleblog.com/2016/05/announcing-syntaxnet-worlds-most.html
  - Netbase, for twitter sentences
  - https://www.codeproject.com/Articles/43372/NetBase-A-Minimal-NET-Database-with-a-Small-SQL
  - Stanford **:** https://nlp.stanford.edu/software/lex-parser.shtml