PCFG Parsing, Evaluation, & Improvements

Ling 571
Deep Processing Techniques for NLP
January 28, 2014

Roadmap

- Parsing PCGFs:
  - Probabilistic CKY parsing
- Evaluation
  - Parseval
- Issues:
  - Positional and lexical independence assumptions
- Improvements:
  - Lexicalization: PLCFGs

Parsing Problem for PCFGs

- Select T such that:

$$\hat{T}(S) = \underset{T s.t, S = yield(T)}{\operatorname{argmax}} P(T)$$

  - String of words S is *yield* of parse tree over S
  - Select tree that maximizes probability of parse

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- Extend existing algorithms: CKY & Earley
  - Most modern PCFG parsers based on CKY
    - Augmented with probabilities

Probabilistic CKY

- Like regular CKY
  - Assume grammar in Chomsky Normal Form (CNF)
    - Productions:
      - A -> B C or A -> w
  - Represent input with indices b/t words
    - E.g., $_0$ Book $_1$ that $_2$ flight $_3$ through $_4$ Houston $_5$

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- For input string length *n* and non-terminals *V*
  - Cell[i,j,A] in (n+1)x(n+1)xV matrix contains
    - Probability that constituent A spans [i,j]

Probabilistic CKY Algorithm

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*]

PCKY Grammar Segment

S	$\rightarrow$	$NP\ VP$	.80	Det	$\rightarrow$	the	.40
NP	$\rightarrow$	$Det\ N$	.30	Det	$\rightarrow$	a	.40
VP	$\rightarrow$	$V\ NP$	.20	N	$\rightarrow$	$meal$	.01
V	$\rightarrow$	$includes$	.05	N	$\rightarrow$	$flight$	.02

PCKY Matrix: The flight includes a meal

Det: 0.4 **[0,1]**				

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			Det: 0.4 [3,4]	

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	N: 0.2 [1,2]	[1,3]	[1,4]	
		V: 0.05 [2,3]	[2,4]	
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		V: 0.05 [2,3]	[2,4]	
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	N: 0.2 [1,2]	[1,3]	[1,4]	
		V: 0.05 [2,3]	[2,4]	VP: 0.2*0.05*0.0012=0.000012 [2,5]
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	N: 0.2 [1,2]	[1,3]	[1,4]	[1,5]
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Probabilistic Parser Development Paradigm

- Training:
  - (Large) Set of sentences with associated parses (Treebank)
    - E.g., Wall Street Journal section of Penn Treebank, sec 2-21
      - 39,830 sentences
    - Used to estimate rule probabilities

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- Test:
  - (Small-med) Set of sentences w/parses (WSJ, 23)
    - 2416 sentences
  - Held out, used for final evaluation

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
- How can we tell how good the parser is?
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- How can we tell how good a parse is?
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  - Partial credit:
    - Constituents in output match those in reference
      - Same start point, end point, non-terminal symbol

Parseval

- How can we compute parse score from constituents?
- Multiple measures:
  - Labeled recall (LR):
    - $\frac{\text{\# of correct constituents in hyp. parse}}{\text{\# of constituents in reference parse}}$

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- Multiple measures:
  - Labeled recall (LR):
    - # of correct constituents in hyp. parse
    - # of constituents in reference parse
  - Labeled precision (LP):
    - # of correct constituents in hyp. parse
    - # of total constituents in hyp. parse

Parseval (cont'd)

- F-measure:
  - Combines precision and recall

$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2(P + R)}$$

  - F1-measure: $\beta = 1$ $\quad F_1 = \frac{2PR}{(P + R)}$

- Crossing-brackets:
  - # of constituents where reference parse has bracketing ((A B) C) and hyp. has (A (B C))

Precision and Recall

- Gold standard
  - (S (NP (A a)) (VP (B b) (NP (C c)) (PP (D d))))
- Hypothesis
  - (S (NP (A a)) (VP (B b) (NP (C c) (PP (D d)))))

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- LP: 4/5
- LR: 4/5
- F1: 4/5

State-of-the-Art Parsing

- Parsers trained/tested on *Wall Street Journal* PTB
  - LR: 90%;
  - LP: 90%;
  - Crossing brackets: 1%

- Standard implementation of Parseval: **evalb**

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  - Extrinsic evaluation
  - How well does this match semantics, etc?

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    - Condition on Subj/Obj with parent annotation

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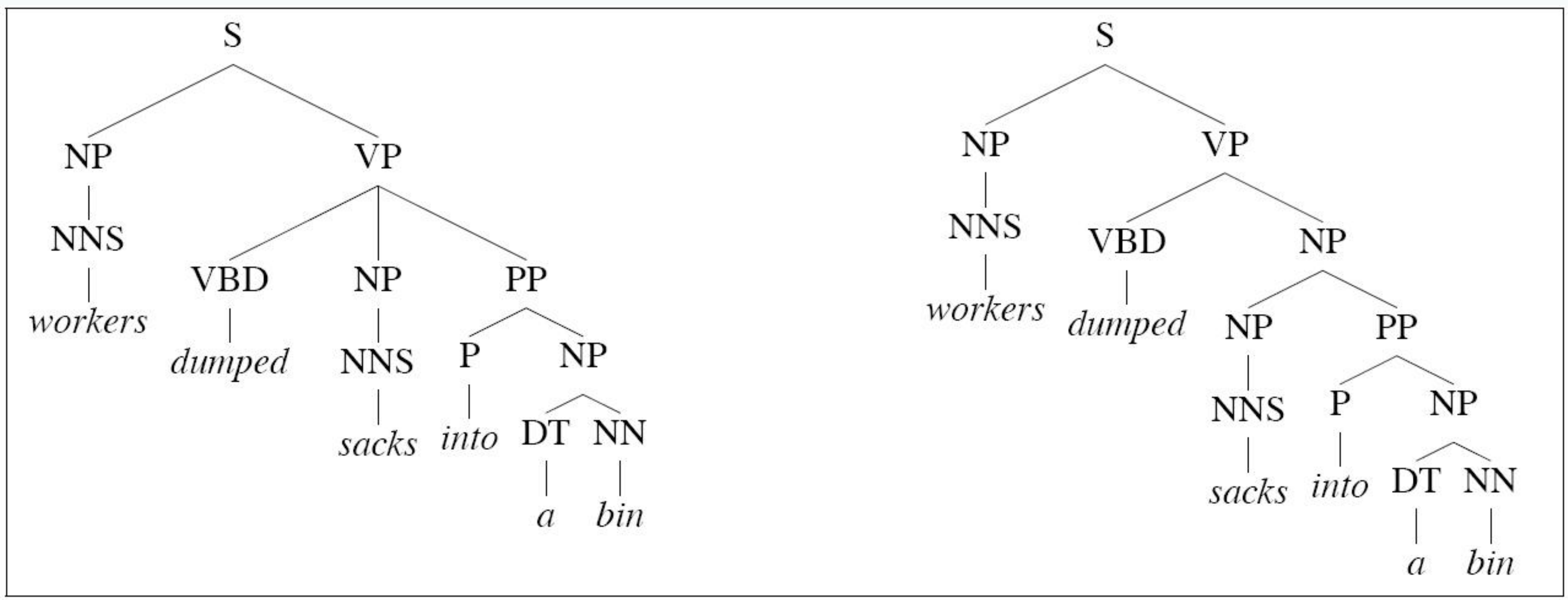

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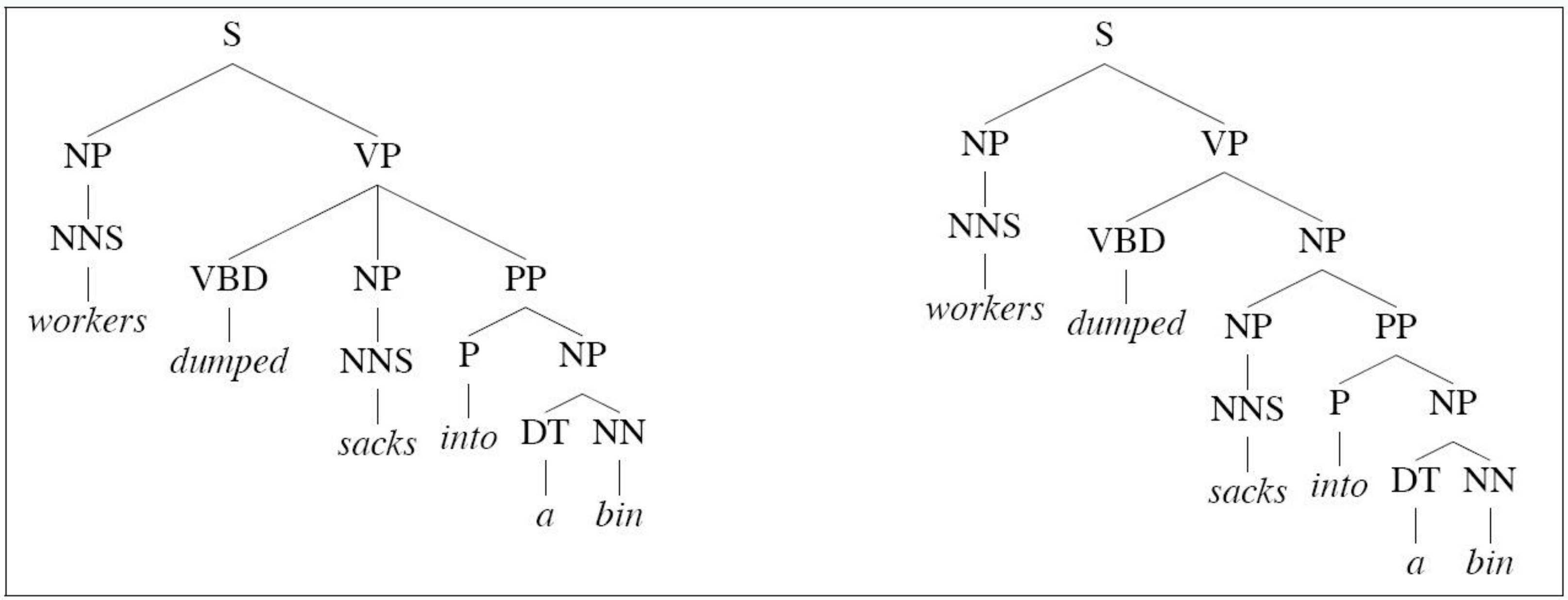

Different verbs & prepositions have different attachment preferences

Parser Issues

- PCFGs make many (unwarranted) independence assumptions
  - Structural Dependency
    - NP -> Pronoun: much more likely in subject position
  - Lexical Dependency
    - Verb subcategorization
    - Coordination ambiguity

Improving PCFGs: Structural Dependencies

- How can we capture Subject/Object asymmetry?
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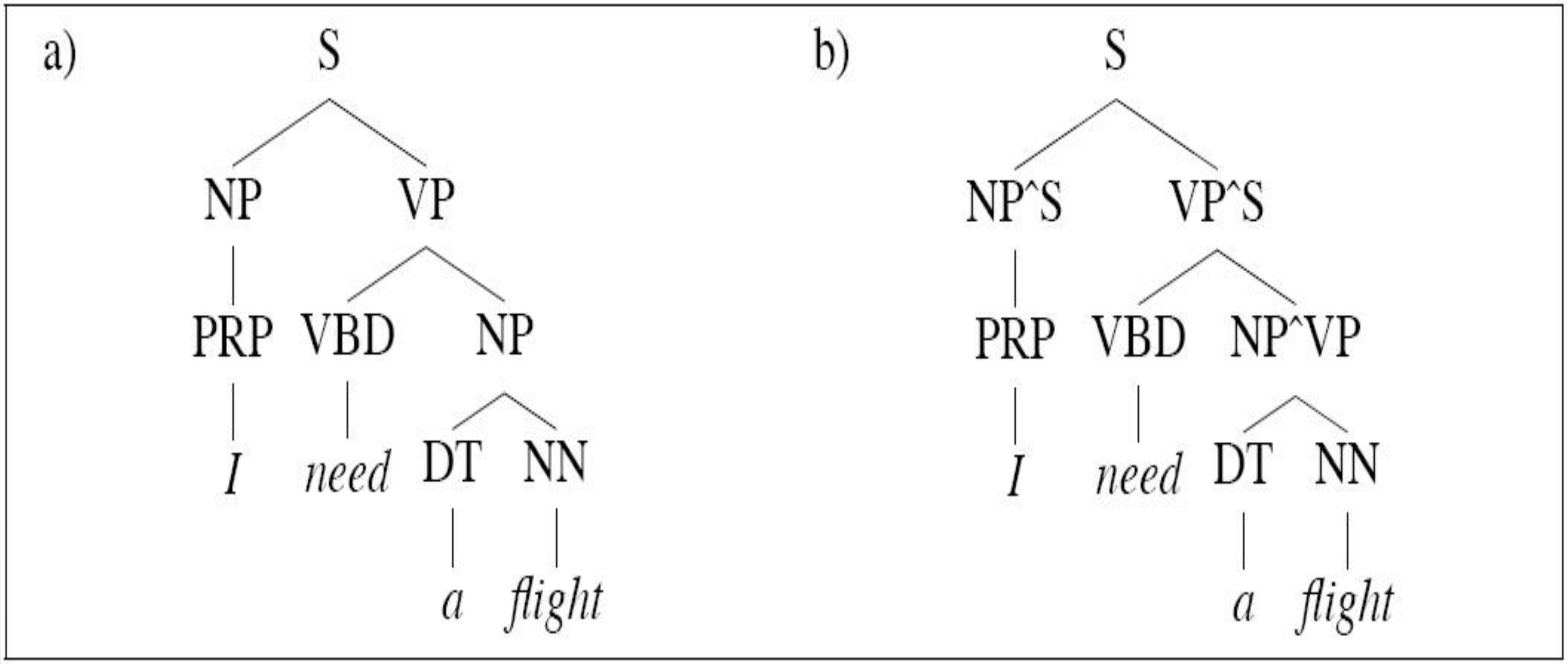
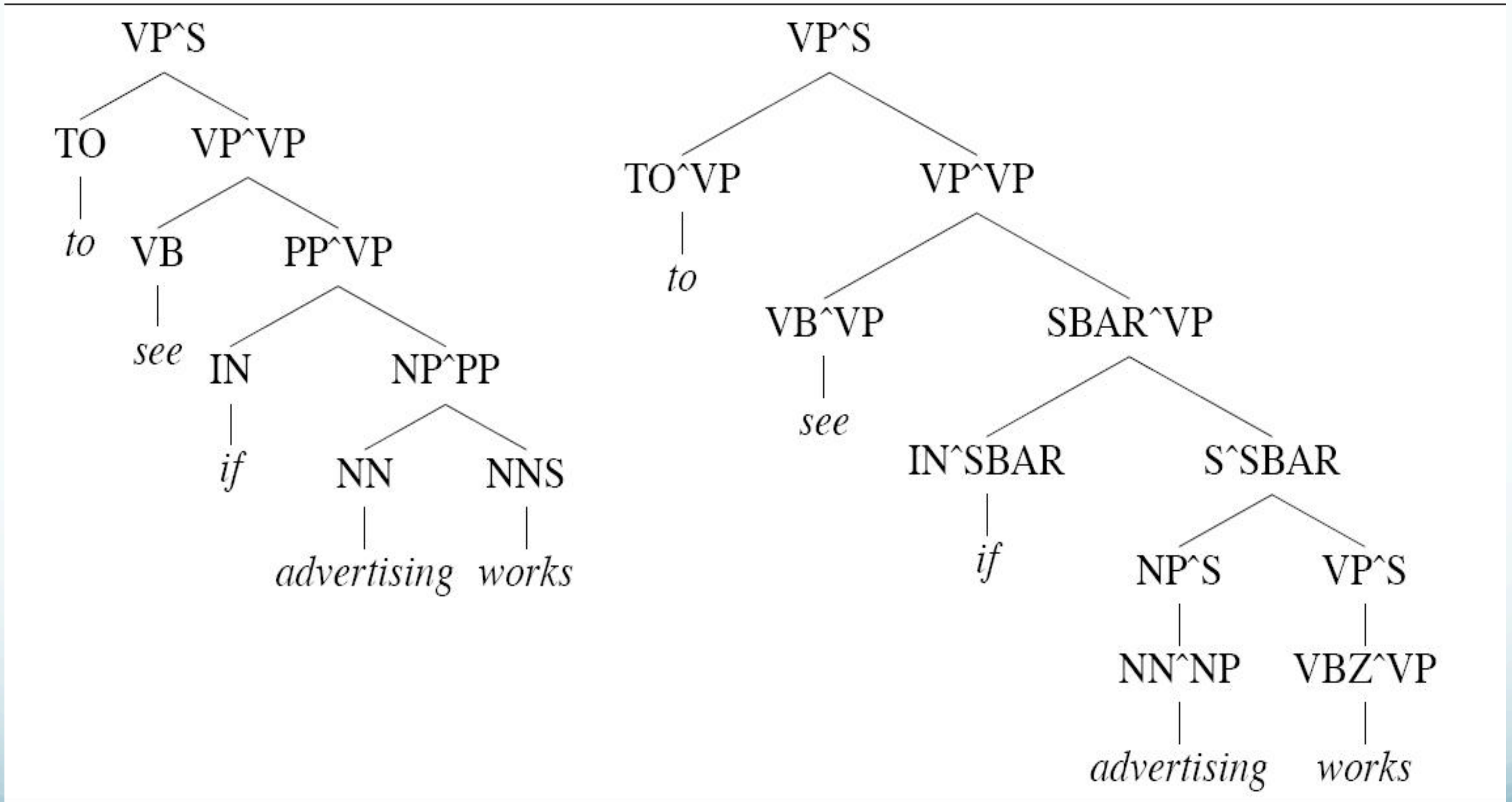
    - E.g., NP^S vs NP^VP
    - Also annotate pre-terminals:
      - RB^ADVP vs RB^VP
      - IN^SBAR vs IN^PP
- Can also split rules on other conditions

Parent Annotation



Parent Annotation: Pre-terminals



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- Disadvantages:
  - Increases number of rules in grammar
  - Decreases amount of training per rule
    - Strategies to search for optimal # of rules

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  - Each rule must identify RHS element as head
    - Heads propagate up tree
  - Conceptually like adding 1 rule per head value
    - VP(dumped) → VBD(dumped)NP(sacks)PP(into)
    - VP(dumped) → VBD(dumped)NP(cats)PP(into)

Lexicalized PCFGs

- Also, add head tag to non-terminals
  - Head tag: Part-of-speech tag of head word
    - VP(dumped) → VBD(dumped)NP(sacks)PP(into)
    - VP(dumped,VBD) → VBD(dumped,VBD)NP(sacks,NNS)PP(into,IN)

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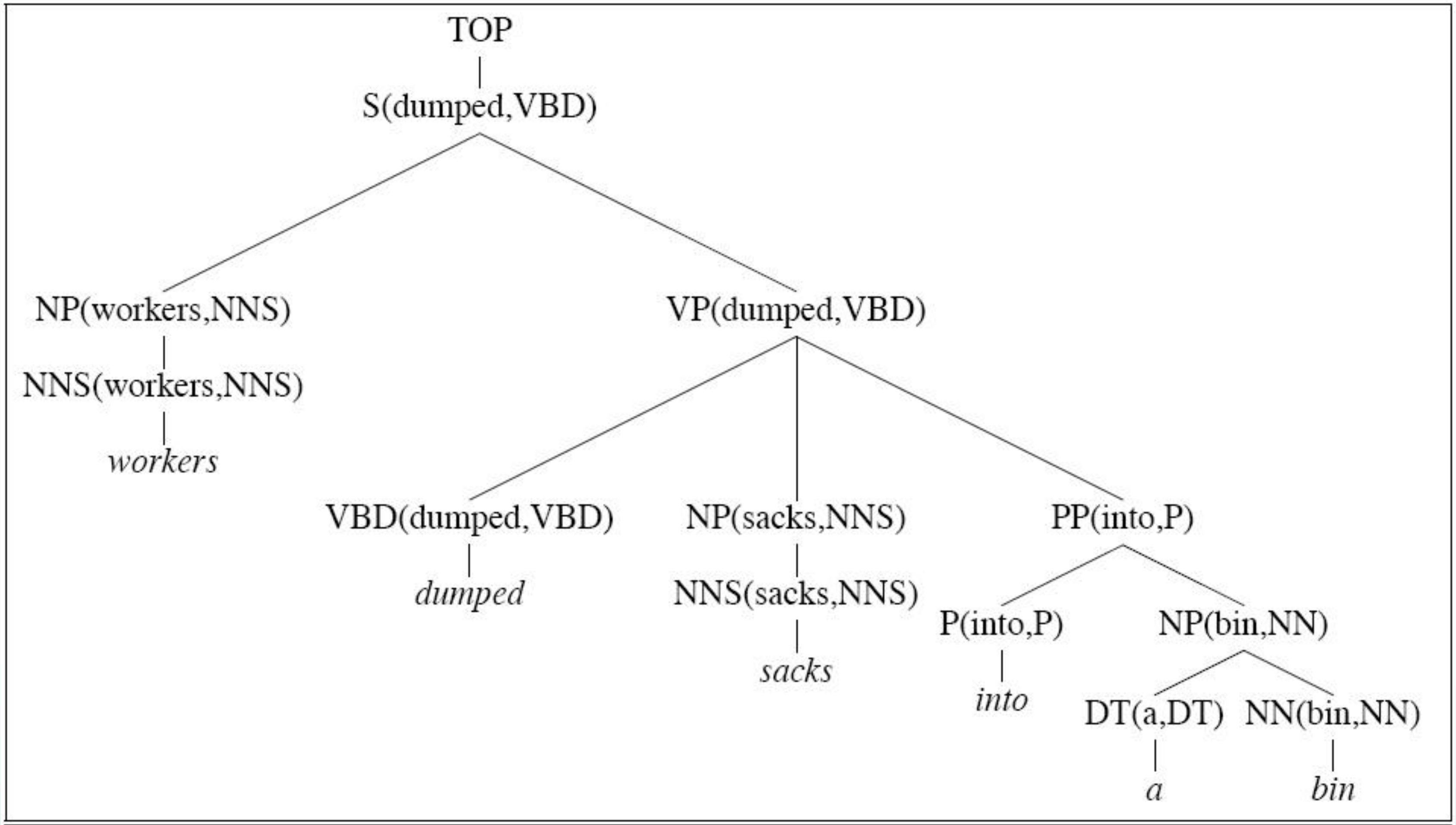
  - Internal rules: all other expansions
    - Must estimate probabilities



Internal Rules					**Lexical Rules**		
TOP	→	S(dumped,VBD)			NNS(workers,NNS)	→	workers
S(dumped,VBD)	→	NP(workers,NNS)	VP(dumped,VBD)		VBD(dumped,VBD)	→	dumped
NP(workers,NNS)	→	NNS(workers,NNS)			NNS(sacks,NNS)	→	sacks
VP(dumped,VBD)	→	VBD(dumped, VBD)	NP(sacks,NNS)	PP(into,P)	P(into,P)	→	into
PP(into,P)	→	P(into,P)	NP(bin,NN)		DT(a,DT)	→	a
NP(bin,NN)	→	DT(a,DT)	NN(bin,NN)		NN(bin,NN)	→	bin

PLCFGs

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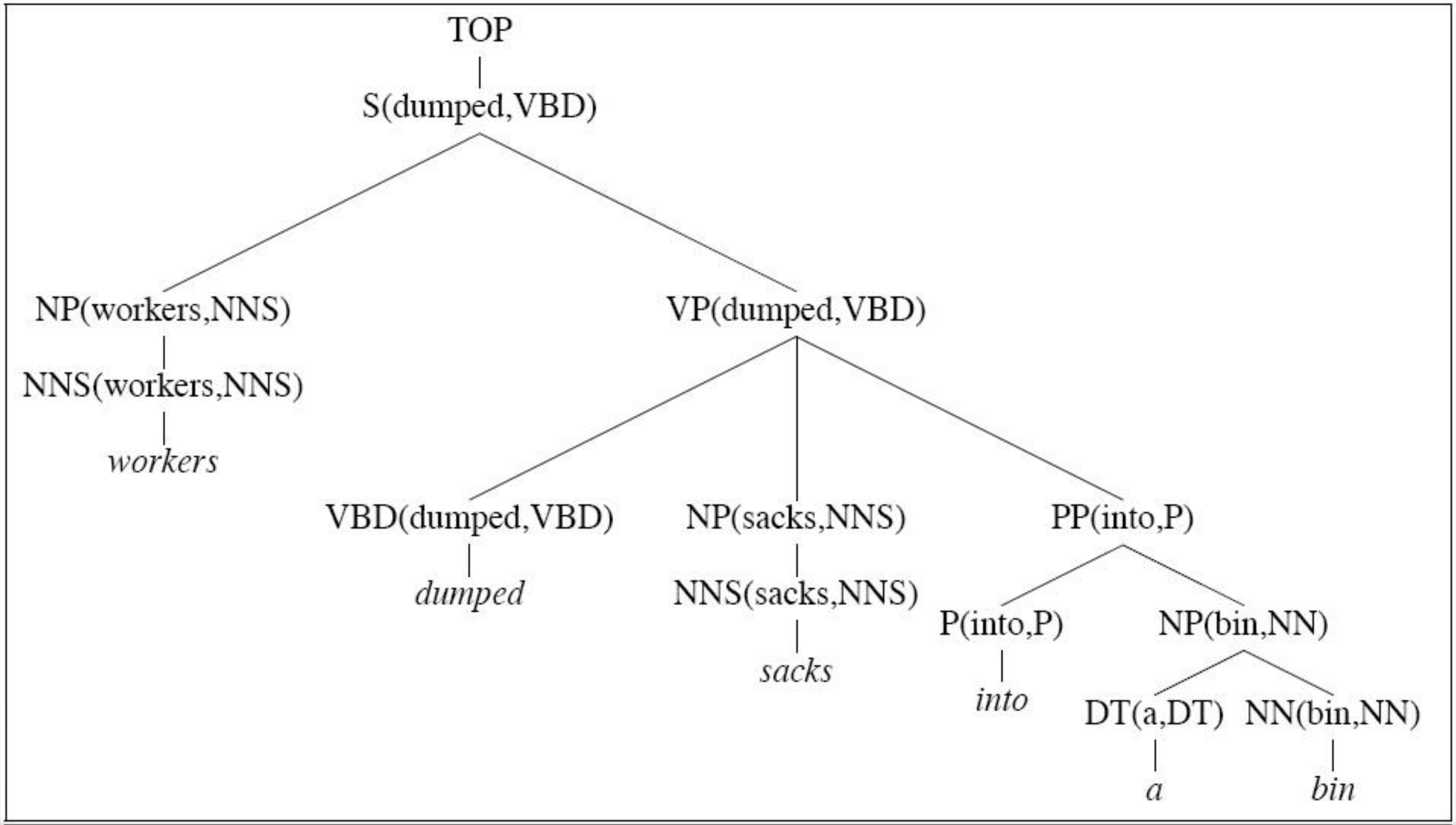
$$P(T,S) = \prod_{n \in T} p(r(n) \mid n, h(n)) * p(h(n) \mid n, h(m(n)))$$


TOP
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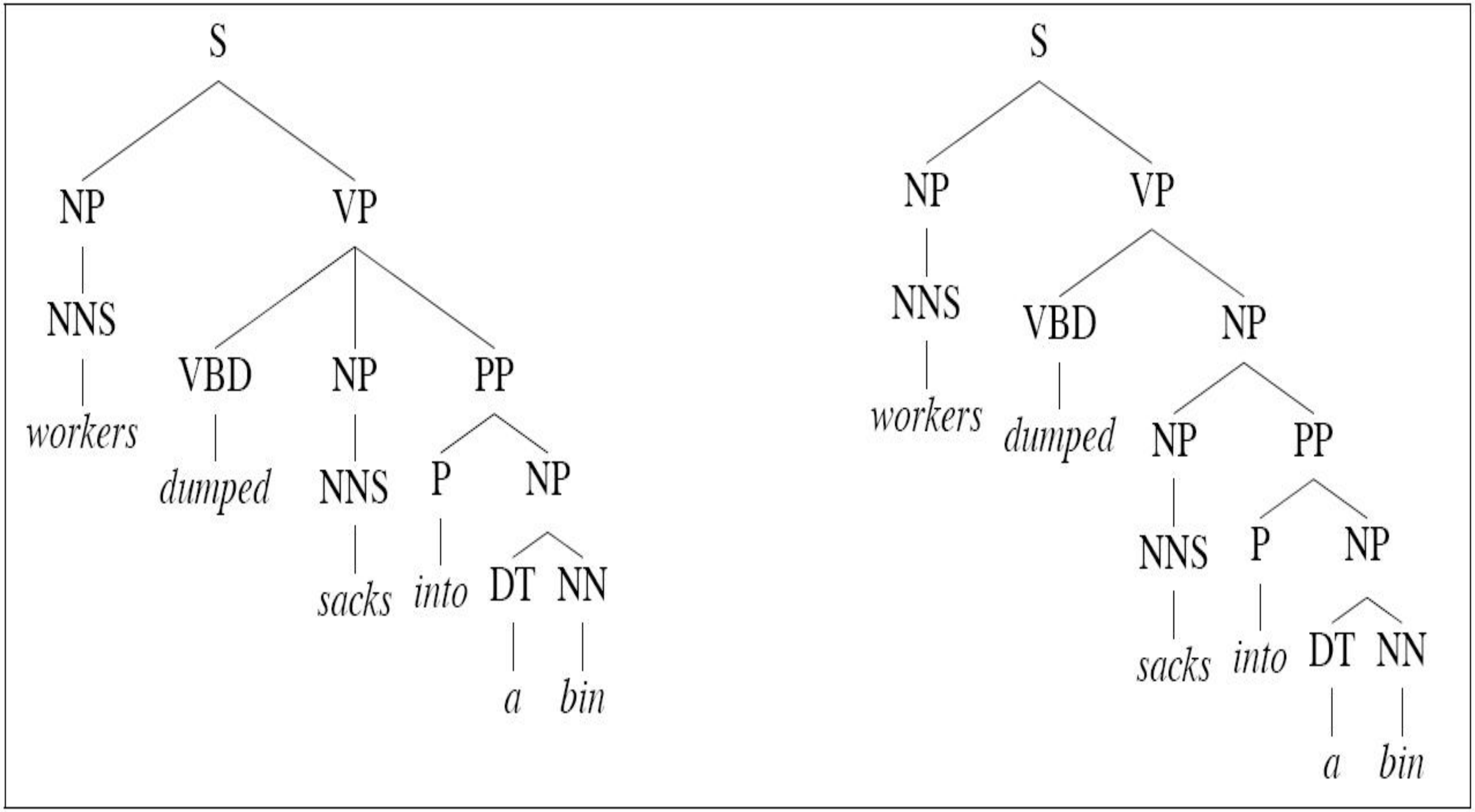
Disambiguation Example



Disambiguation Example

$$P(VP \rightarrow VBDNPPP \mid VP, dumped)$$
$$= \frac{C(VP(dumped) \rightarrow VBDNPP)}{\sum_{\beta} C(VP(dumped) \rightarrow \beta)}$$
$$= 6/9 = 0.67$$

$$p(VP \rightarrow VBDNP \mid VP, dumped)$$
$$= \frac{C(VP(dumped) \rightarrow VBDNP)}{\sum_{\beta} C(VP(dumped) \rightarrow \beta)}$$
$$= 0/9 = 0$$

$$p(in \mid PP, dumped)$$
$$= \frac{C(X(dumped) \rightarrow ...PP(in)..)}{\sum_{\beta} C(X(dumped) \rightarrow ...PP...)}$$
$$= 2/9 = 0.22$$

$$p(in \mid PP, sacks)$$
$$= \frac{C(X(sacks) \rightarrow ...PP(in)...)}{\sum_{\beta} C(X(sacks) \rightarrow ...PP...)}$$
$$= 0/0$$

CNF Factorization & Markovization

- CNF factorization:
  - Converts n-ary branching to binary branching

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  - Can maintain information about original structure
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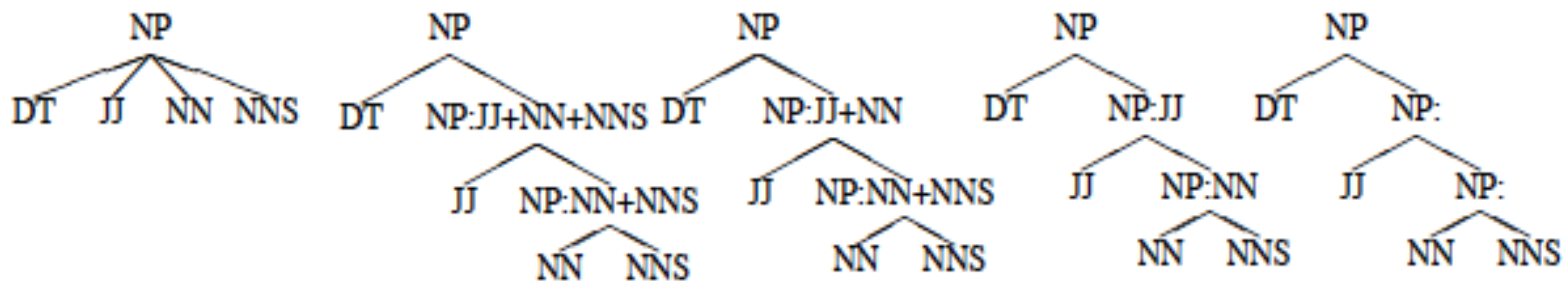
  - How much context should we keep?
    - What Markov order?

Different Markov Orders



(a) (b) (c) (d) (e)

Markovization & Costs

(Mohri & Roark 2006)

PCFG	Time (s)	Words/s	$\|V\|$	$\|P\|$	LR	LP	F
Right-factored	4848	6.7	10105	23220	69.2	73.8	71.5
Right-factored, Markov order-2	1302	24.9	2492	11659	68.8	73.8	71.3
Right-factored, Markov order-1	445	72.7	564	6354	68.0	73.0	70.5
Right-factored, Markov order-0	206	157.1	99	3803	61.2	65.5	63.3
Parent-annotated, Right-factored, Markov order-2	7510	4.3	5876	22444	76.2	78.3	77.2

Improving PCFGs: Tradeoffs

- Tensions:
  - Increase accuracy:
    - Increase specificity
      - E.g. Lexicalizing, Parent annotation, Markovization,etc
  - Increases grammar
    - Increases processing times
    - Increases training data requirements
- How can we balance?

Efficiency

- PCKY is $|G|n^3$
  - Grammar can be huge
  - Grammar can be extremely ambiguous
    - 100s of analyses not unusual, esp. for long sentences
- However, only care about best parses
  - Others can be pretty bad
- Can we use this to improve efficiency?

Beam Thresholding

- Inspired by beam search algorithm

- Assume low probability partial parses unlikely to yield high probability overall
  - Keep only top k most probably partial parses
    - Retain only k choices per cell
      - For large grammars, could be 50 or 100
      - For small grammars, 5 or 10

Heuristic Filtering

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- Exclusions:
  - Low frequency: exclude singleton productions
  - Low probability: exclude constituents x s.t. $p(x) < 10^{-200}$
  - Low relative probability:
    - Exclude x if there exists y s.t. $p(y) > 100 * p(x)$

Notes on HW#3

- Outline:
  - Induce grammar from (small) treebank
  - Implement Probabilistic CKY
  - Evaluate parser
  - Improve parser

Treebank Format

- Adapted from Penn Treebank Format

  - Rules simplified:
    - Removed traces and other null elements
    - Removed complex tags
    - Reformatted POS tags as non-terminals

Reading the Parses

- POS unary collapse:
  - (NP_NNP Ontario)
    - was
  - (NP (NNP Ontario))

- Binarization:
  - VP -> VP’ PP; VP’ -> VB PP
    - Was
  - VP -> VB PP PP

Start Early!