Probabilistic Parsing: Evaluation & Improvement

Ling571
Deep Processing Techniques for NLP
January 26, 2015

Roadmap

- Probabilistic Parsing:
  - Evaluation: Parseval
  - Limitations of PCFGs
  - Improvements on PCFGs
    - Parent annotation
    - Lexicalization

Parser Evaluation

- Assume a ‘gold standard’ set of parses for test set
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  - Partial credit:
    - Constituents in output match those in reference
      - Same start point, end point, non-terminal symbol

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

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
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- 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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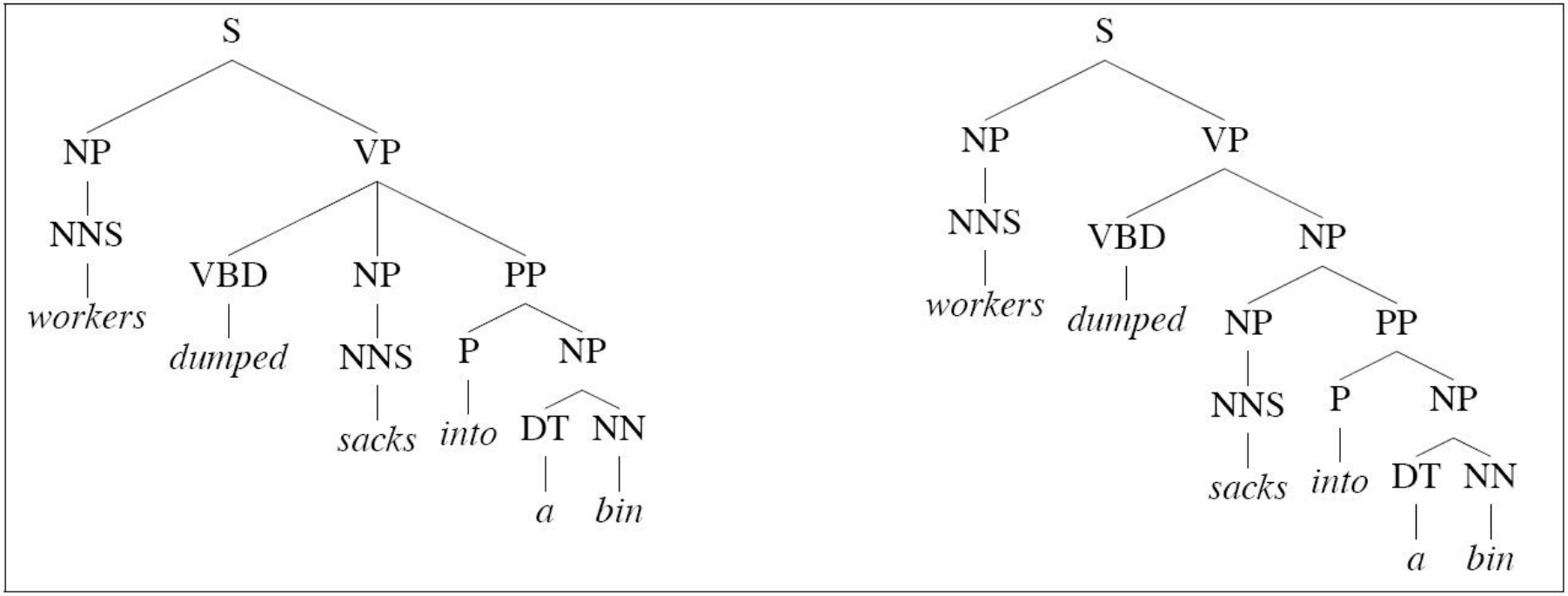

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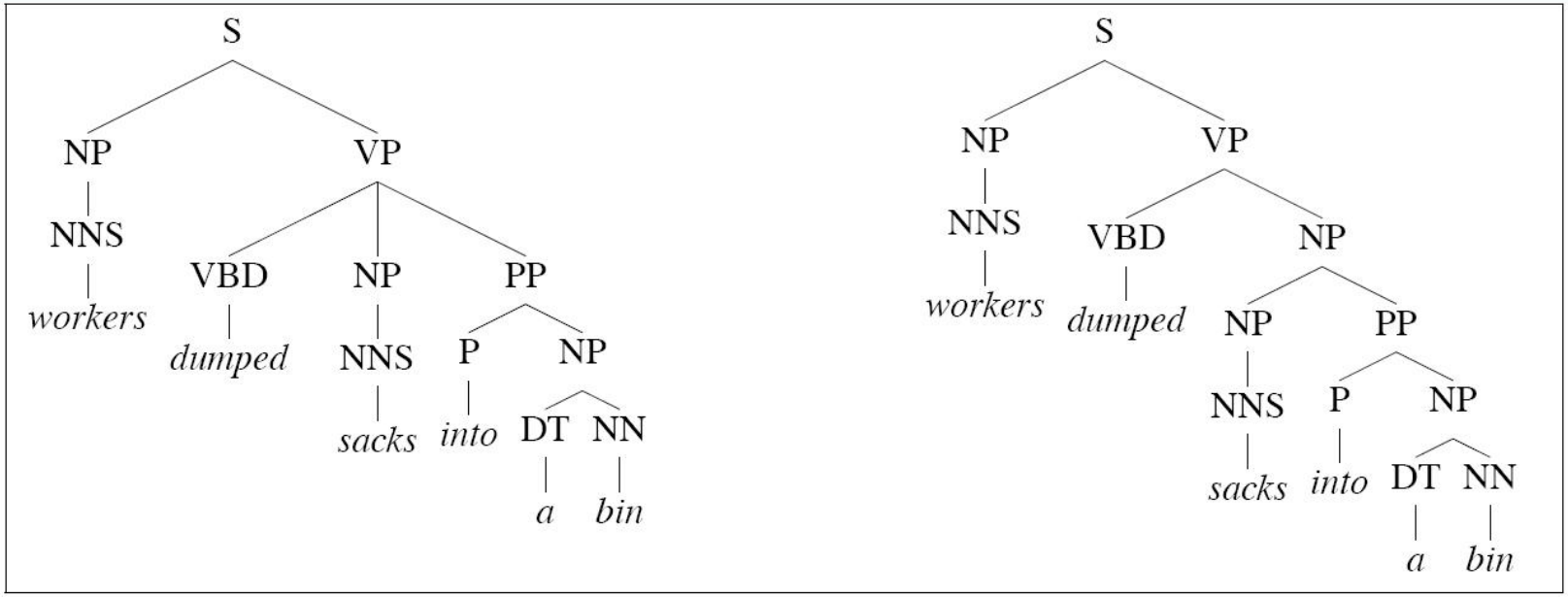

Different verbs & prepositions have different attachment preferences

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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- Parent annotation:
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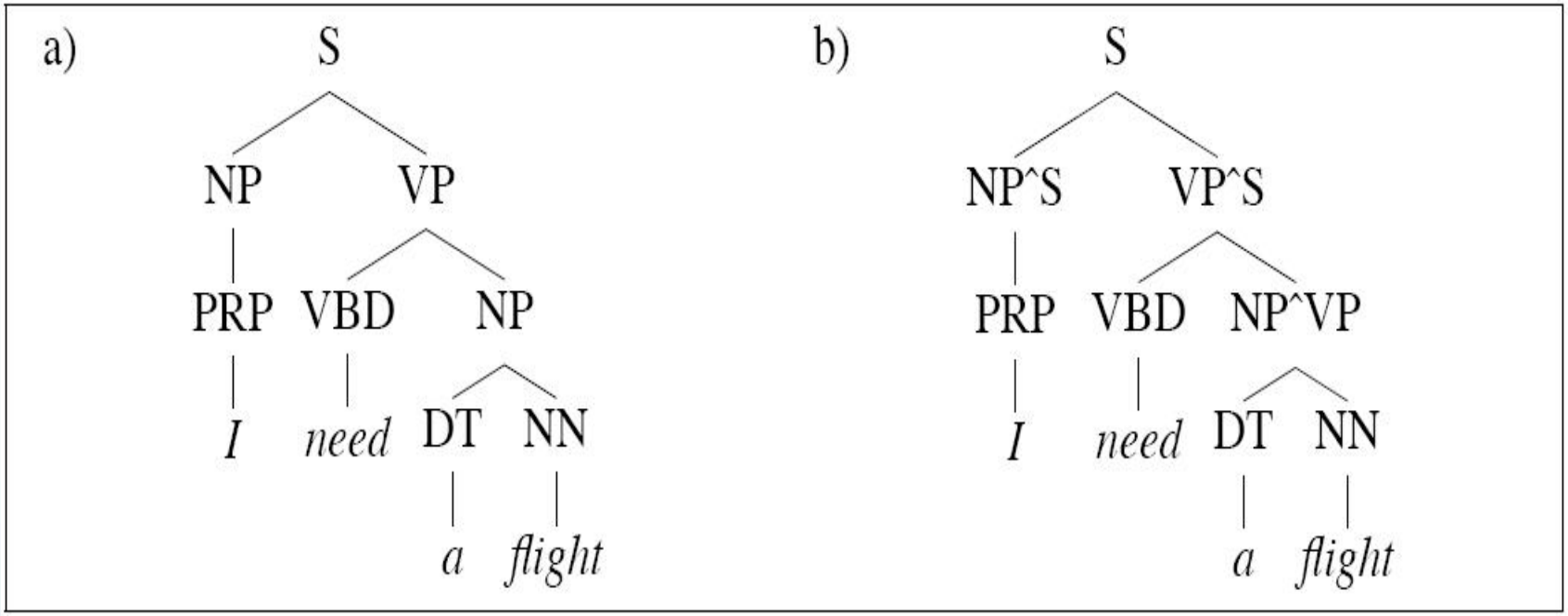
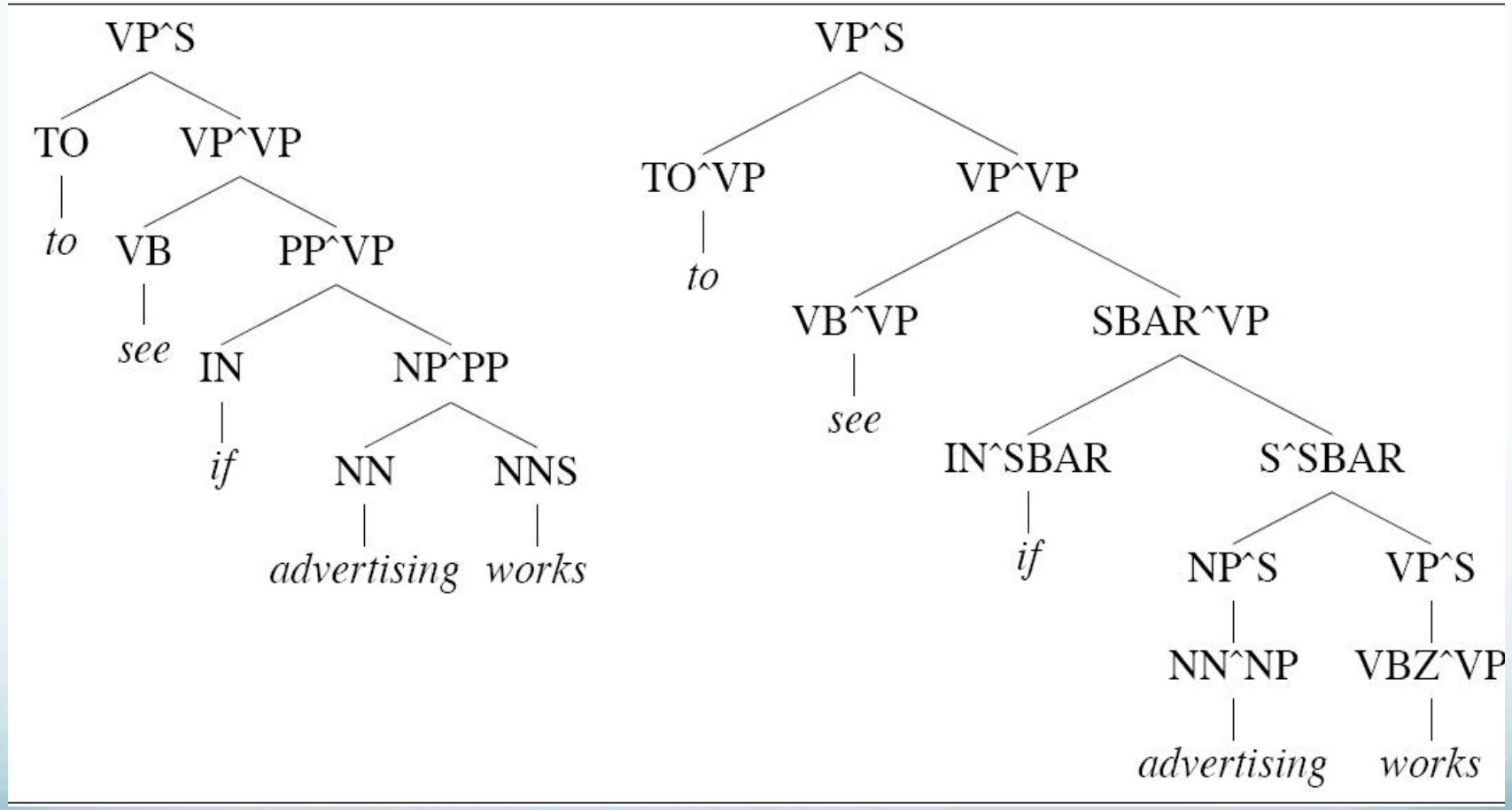
    - E.g., NP^S vs NP^VP
    - Also annotate pre-terminals:
      - RB^ADVP vs RB^VP
      - IN^SBAR vs IN^PP
- Can also split rules on other conditions

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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    - 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
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    - VP(dumped,VBD) → VBD(dumped,VBD)NP(sacks,NNS)PP(into,IN)

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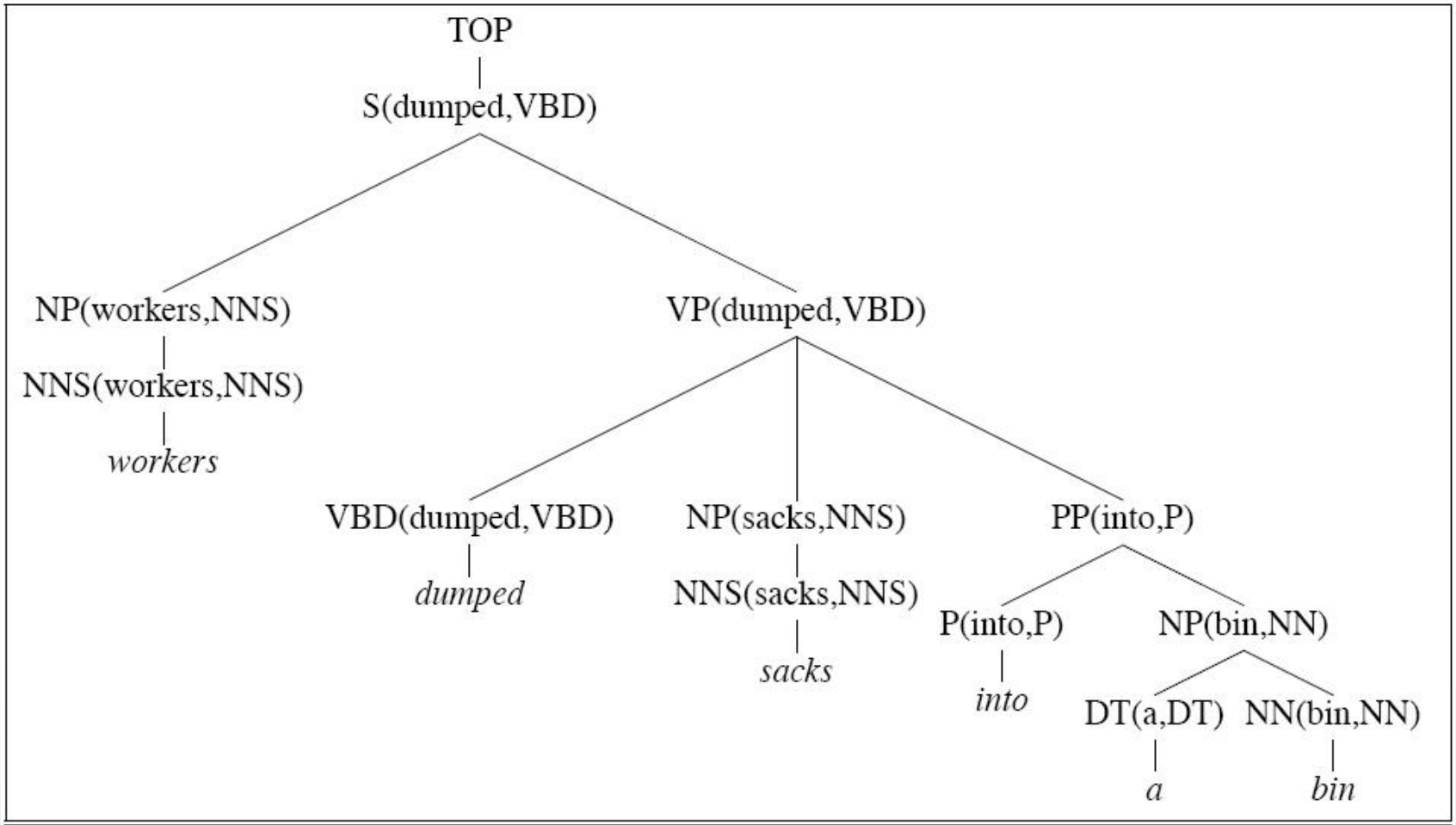
    - Must estimate probabilities



Internal Rules

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

Lexical Rules

NNS(workers,NNS)	→	workers
VBD(dumped,VBD)	→	dumped
NNS(sacks,NNS)	→	sacks
P(into,P)	→	into
DT(a,DT)	→	a
NN(bin,NN)	→	bin

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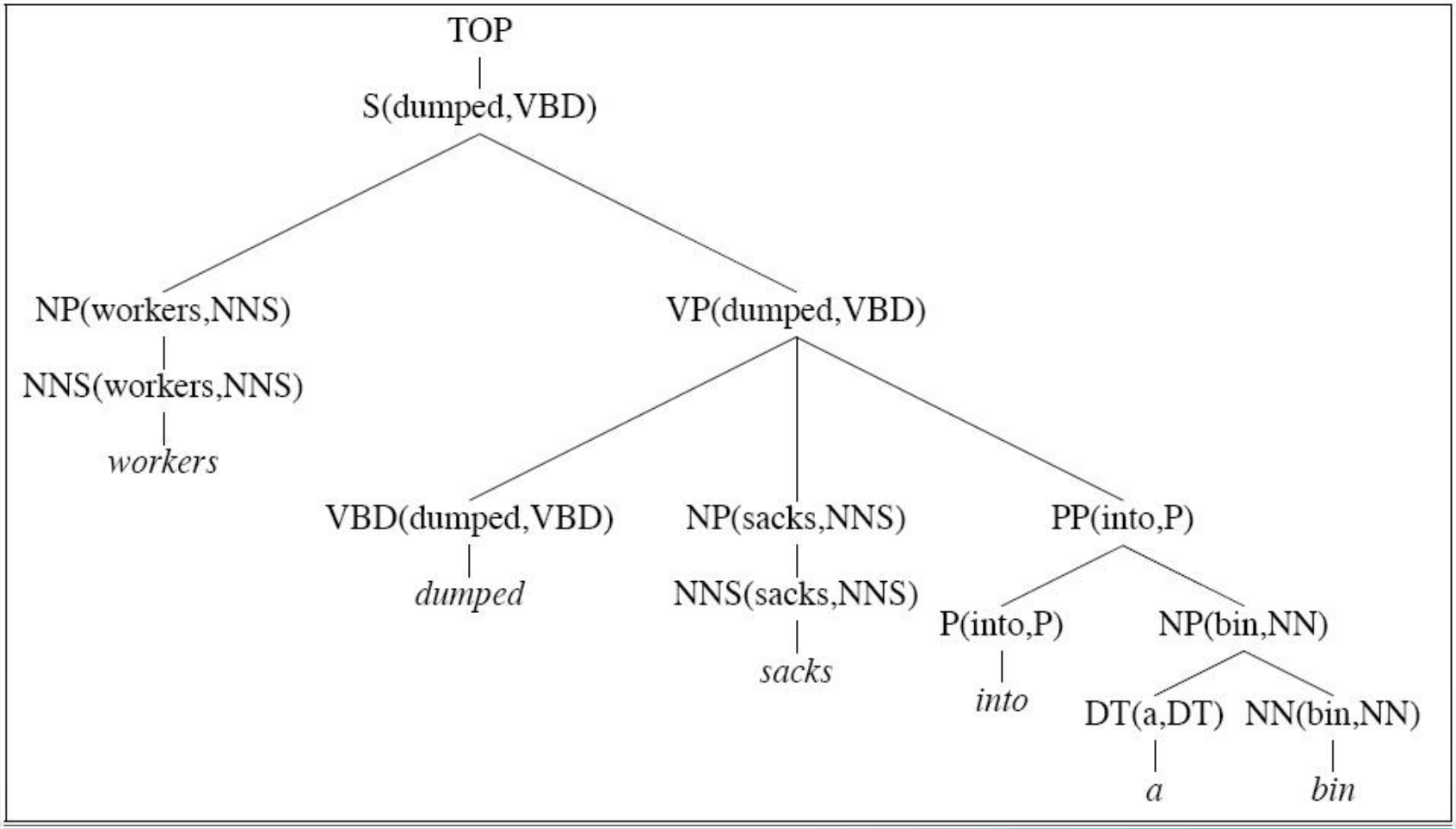
$$P(T,S) = \prod_{n \in T} p(r(n) \mid n, h(n)) * p(h(n) \mid n, h(m(n)))$$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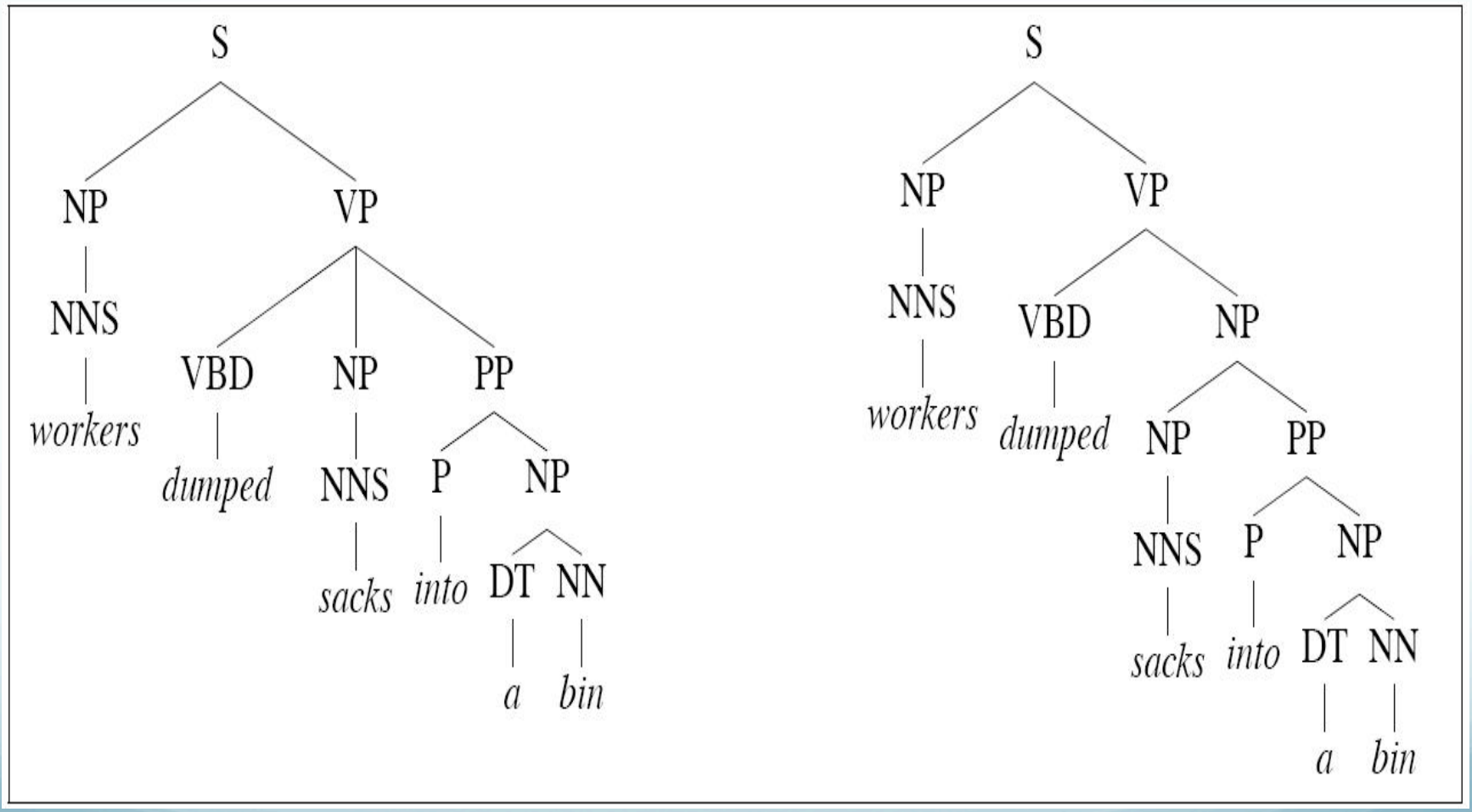
Disambiguation Example



Disambiguation Example

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

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

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

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

CNF Factorization & Markovization

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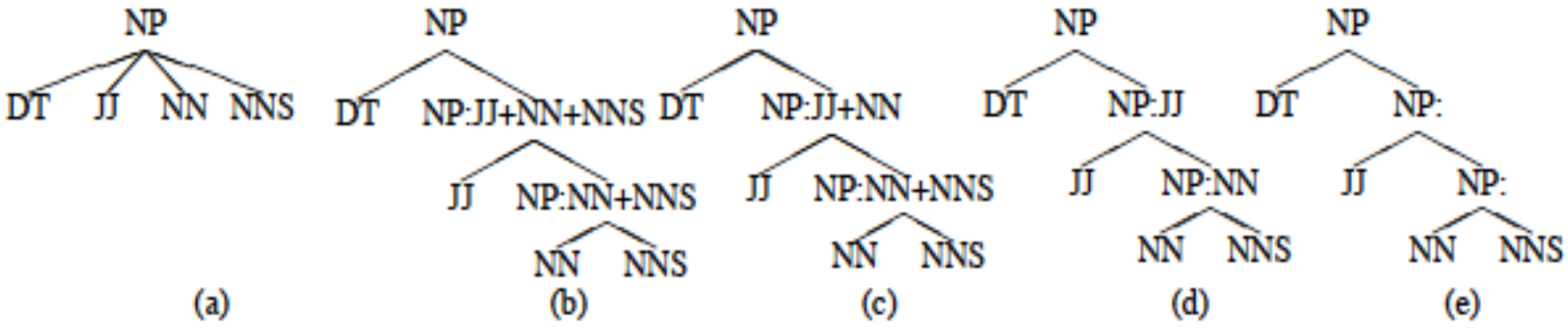
      - If keep all context: 72 -> 10K non-terminals!!!
  - How much context should we keep?
    - What Markov order?

Different Markov Orders



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

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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. $p(y) > 100 * p(x)$

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  - Approaches create new rules incorporating context:
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  - Other problems:
    - Increase rules, sparseness
- Need approach that incorporates broader, global info

Discriminative Parse Reranking

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- Discriminative reranking
  - Use arbitrary features in reranker (MaxEnt)
    - E.g. right-branching-ness, speaker identity, conjunctive parallelism, fragment frequency, etc

Reranking Effectiveness

- How can reranking improve?
  - N-best includes the correct parse
- Estimate maximum improvement
  - **Oracle** parse selection
    - Selects correct parse from N-best
      - If it appears
- E.g. Collins parser (2000)
  - Base accuracy: 0.897
  - Oracle accuracy on 50-best: 0.968
- Discriminative reranking: 0.917