Probabilistic Parsing: Issues & Improvement

Deep Processing Techniques for NLP
Ling571
January 25, 2017

Roadmap

- Probabilistic Parsing:
  - PCFG issues
  - Modeling improvements on PCFGs
    - Parent annotation
    - Lexicalization
    - Markovization
    - Reranking

  - Efficiency improvements on PCFGs
    - Beam thresholding
    - Heuristic filtering

Issues with PCFGs

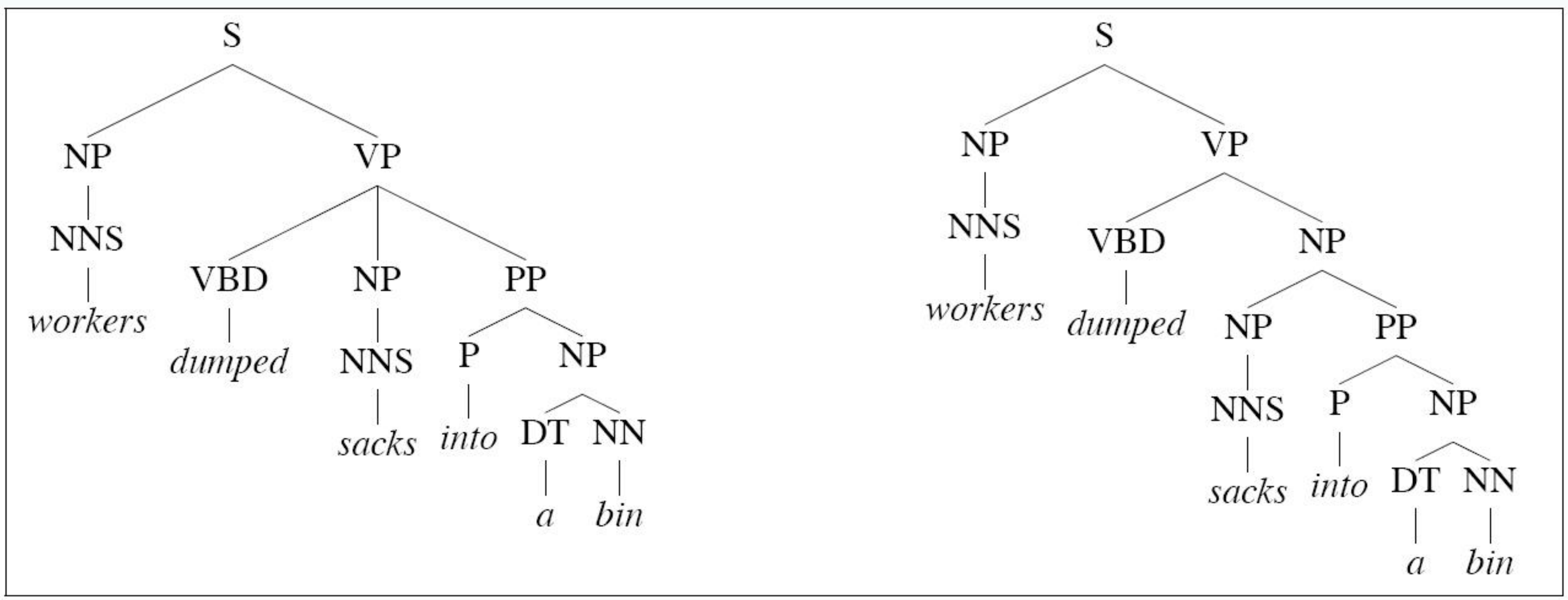
- Independence assumptions:
  - Rule expansion is context-independent
    - Allows us to multiply probabilities
  - Is this valid?

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

    - In Treebank: roughly equi-probable
  - How can we handle this?
    - Condition on Subj/Obj with parent annotation

Issues with PCFGs

- Insufficient lexical conditioning
  - Present in pre-terminal rules
- Are there cases where other rules should be conditioned on words?



Different verbs & prepositions have different attachment preferences

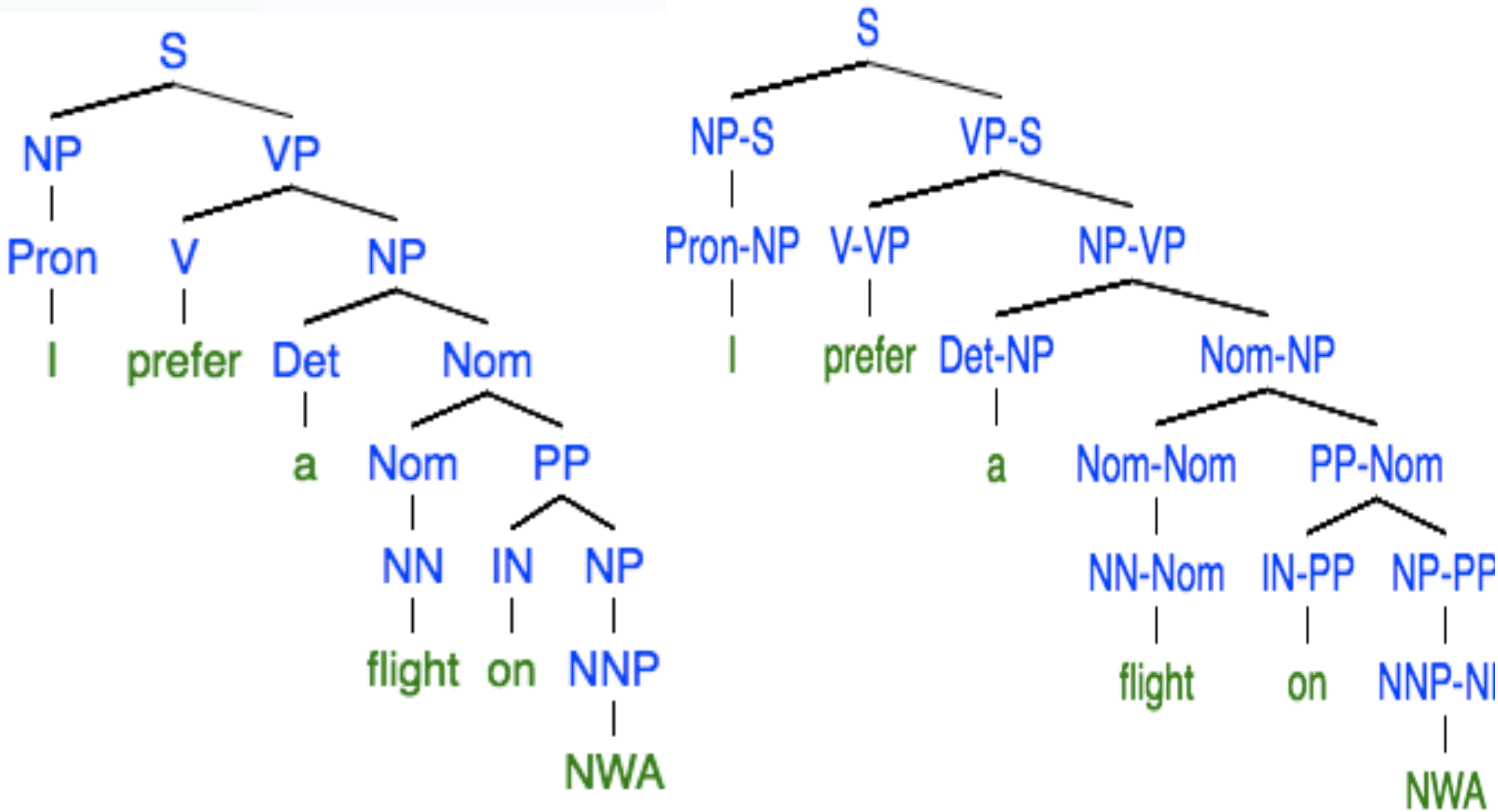
Parser Issues

- 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?
  - E.g., $NP_{subj} \rightarrow$ Pron vs $NP_{Obj} \rightarrow$ Pron
- Parent annotation:
  - Annotate each node with parent in parse tree
    - 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

- Advantages:
  - Captures structural dependency in grammars

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

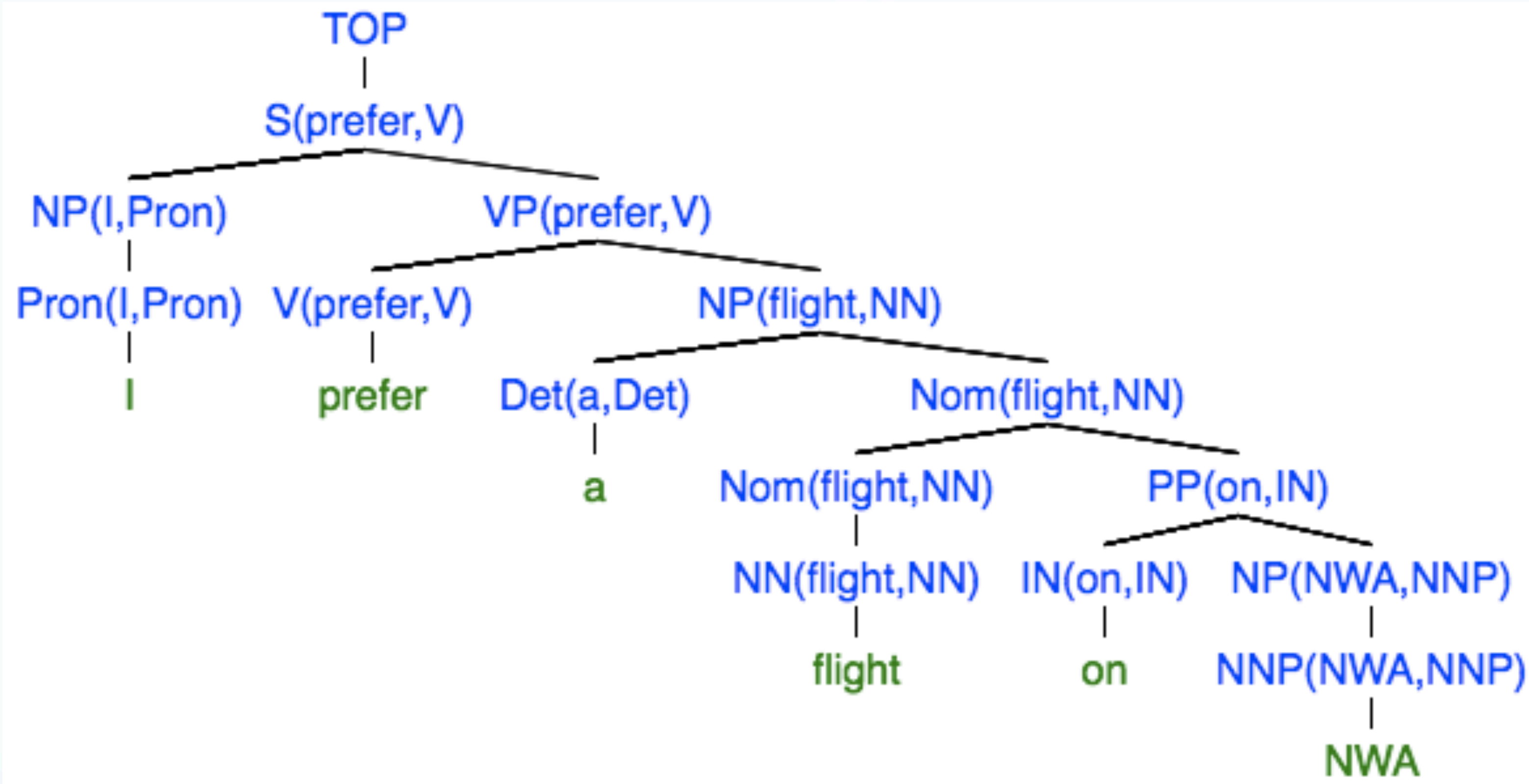
Improving PCFGs: Lexical Dependencies

- Lexicalized rules:
  - Best known parsers: Collins, Charniak parsers
  - Each non-terminal annotated with its lexical head
    - E.g. verb with verb phrase, noun with noun phrase
  - 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)
- Two types of rules:
  - Lexical rules: pre-terminal → word
    - Deterministic, probability 1
  - Internal rules: all other expansions
    - Must estimate probabilities

Lexicalized Parse Tree



Internal Rules

Top → S(prefer,V)
S(prefer,V) → NP(I,Pron) VP(prefer,V)
NP(I,Pron) → Pron(I,Pron)
VP(prefer,V) → V(prefer,V) NP(flight,NN)
NP(flight,NN) → Det(a,Det) Nom(flight,NN)
PP(on,IN) → IN(on,IN) NP(NWA,NNP)

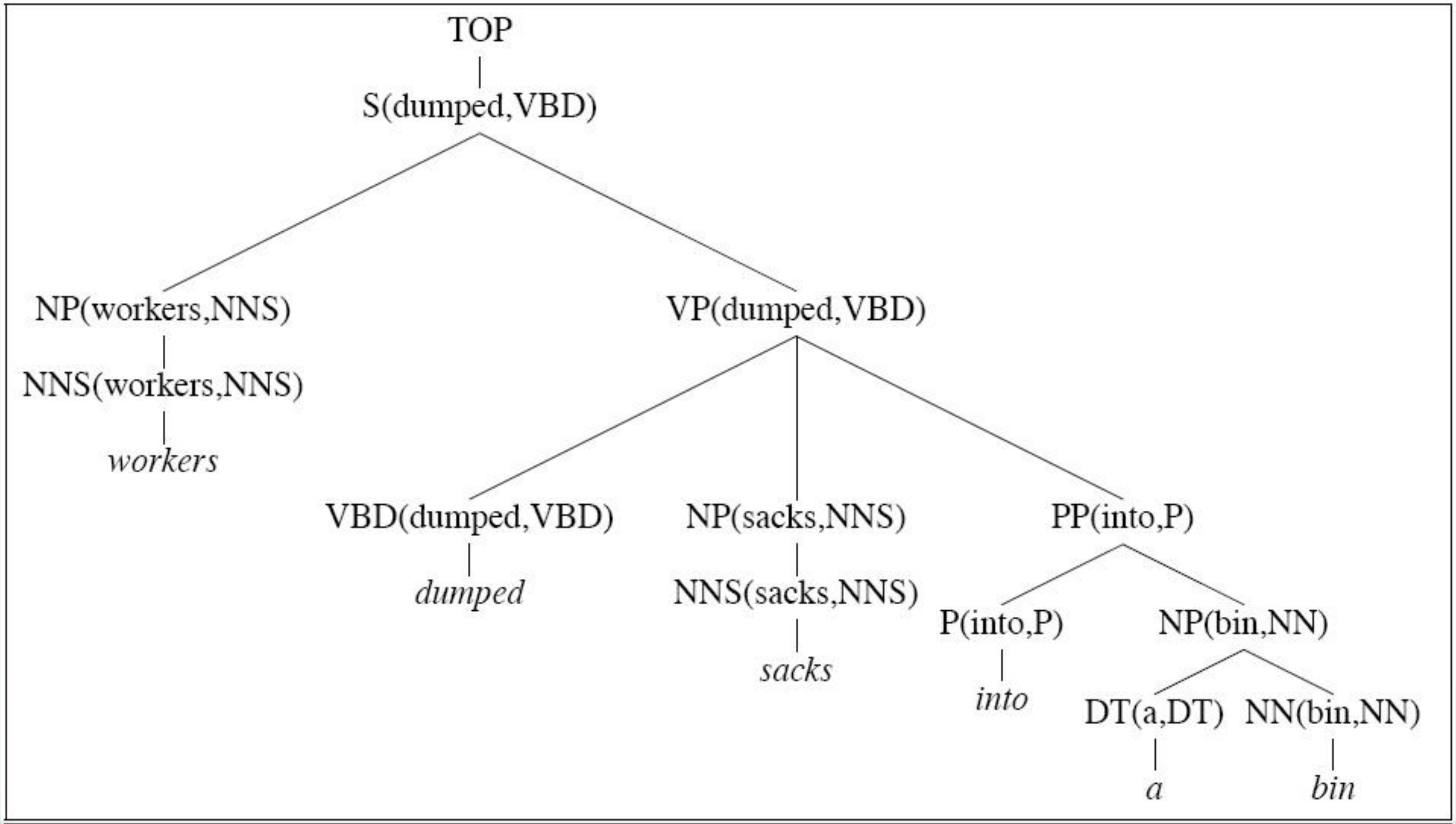
Lexical Rules

Pron(I,Pron) → I
V(prefer,V) → prefer
Det(a,Det) → a
NN(flight,NN) → flight
IN(on,IN) → on
NNP(NWA,NNP) → NWA

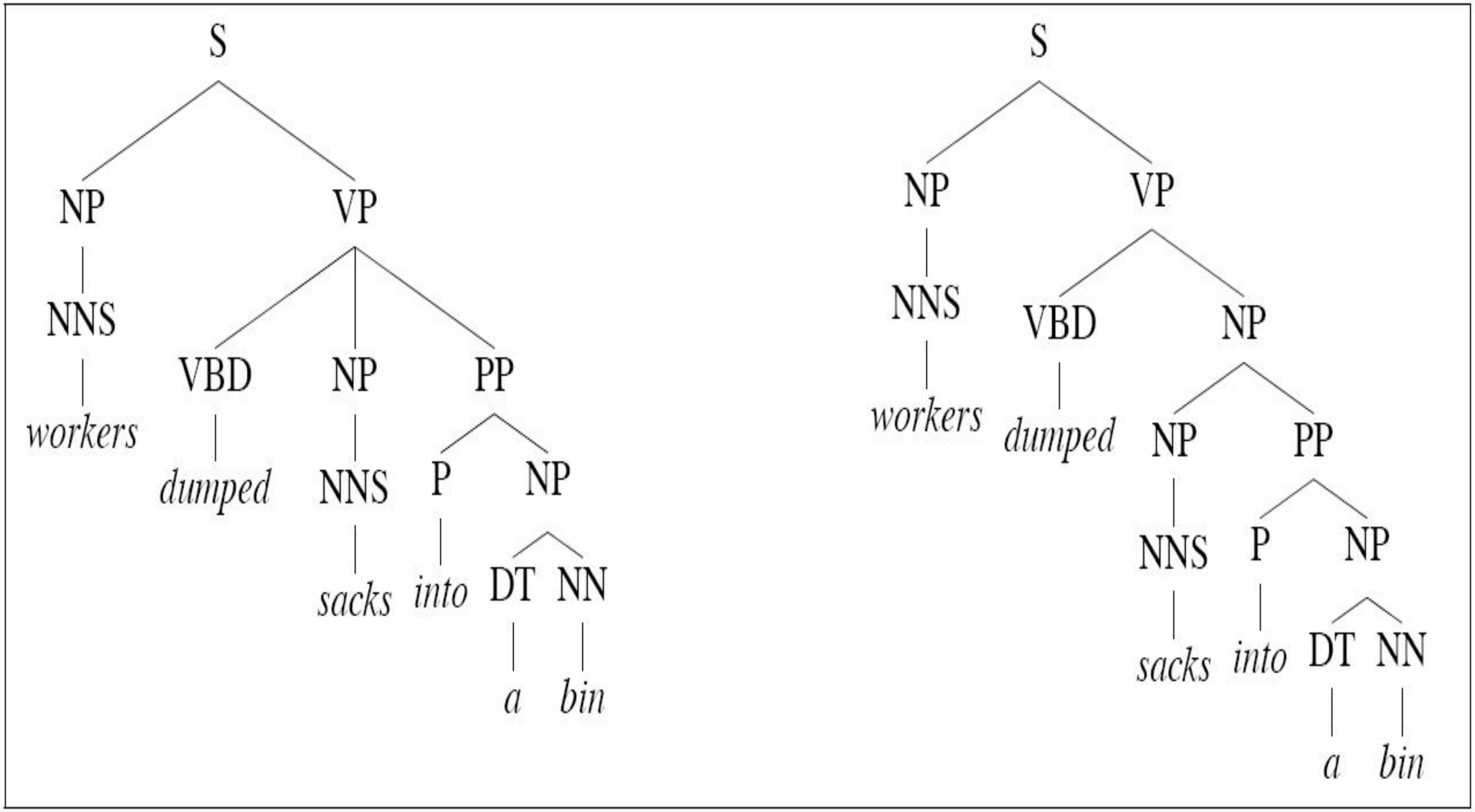
PLCFGs

- Issue: Too many rules
  - No way to find corpus with enough examples
- (Partial) Solution: Independence assumed
  - Condition rule on
    - Category of LHS, head
  - Condition head on
    - Category of LHS and parent's head

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


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

Disambiguation Example



Disambiguation Example

$$P(VP \to VBD\,NP\,PP \mid VP, dumped)$$
$$= \frac{C(VP(dumped) \to VBD\,NP\,PP)}{\sum_{\beta} C(VP(dumped) \to \beta)}$$
$$= 6/9 = 0.67$$

$$p(VP \to VBD\,NP \mid VP, dumped)$$
$$= \frac{C(VP(dumped) \to VBD\,NP)}{\sum_{\beta} C(VP(dumped) \to \beta)}$$
$$= 0/9 = 0$$

$$p(\text{into} \mid PP, dumped)$$
$$= \frac{C(X(dumped) \to \ldots PP(\text{into})..)}{\sum_{\beta} C(X(dumped) \to \ldots PP\ldots)}$$
$$= 2/9 = 0.22$$

$$p(\text{into} \mid PP, sacks)$$
$$= \frac{C(X(sacks) \to \ldots PP(\text{into})\ldots)}{\sum_{\beta} C(X(sacks) \to \ldots PP\ldots)}$$
$$= 0/0$$

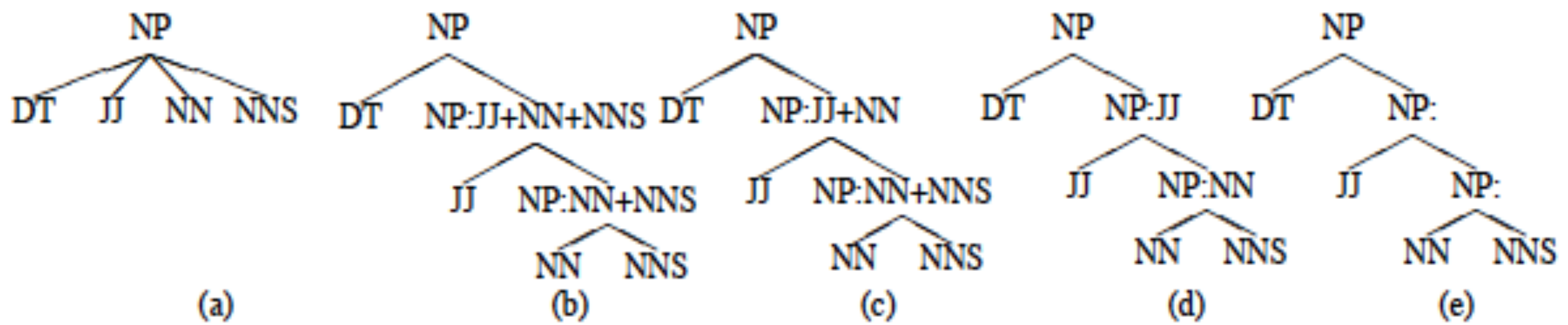
CNF Factorization & Markovization

- CNF factorization:
  - Converts n-ary branching to binary branching
  - Can maintain information about original structure
    - Neighborhood history and parent

  - Issue:
    - Potentially explosive
      - 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

Heuristic Filtering

- Intuition: Some rules/partial parses are unlikely to end up in best parse. Don't store those in table.

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

Reranking

- Issue: Locality
  - PCFG probabilities associated with rewrite rules
  - Context-free grammars
  - Approaches create new rules incorporating context:
    - Parent annotation, Markovization, lexicalization
  - Other problems:
    - Increase rules, sparseness
- Need approach that incorporates broader, global info

Discriminative Parse Reranking

- General approach:
  - Parse using (L)PCFG
  - Obtain top-N parses
  - Re-rank top-N parses using better features
- 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