Probabilistic context-free parsing

Parsing
ISCL-BA-06

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Seminar für Sprachwissenschaft

Winter Semester 2020/21

version: 0bcd8cd+ @2021-01-21

Context-free grammars

recap

- Context free (CF) grammars are most practically useful grammars in the Chomsky hierarchy
- Most of the parsing theory (and practice) is build on parsing CF languages
- The context-free rules have the form

$$A \rightarrow \alpha$$

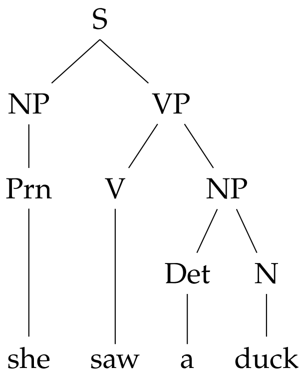
where A is a single non-terminal symbol and α is a (possibly empty) sequence of terminal or non-terminal symbols

An example context-free grammar

S $\rightarrow$ NP VP
S $\rightarrow$ Aux NP VP
NP $\rightarrow$ Det N
NP $\rightarrow$ Prn
NP $\rightarrow$ NP PP
VP $\rightarrow$ V NP
VP $\rightarrow$ V
VP $\rightarrow$ VP PP
PP $\rightarrow$ Prp NP
N $\rightarrow$ duck
N $\rightarrow$ park
N $\rightarrow$ parks
V $\rightarrow$ duck
V $\rightarrow$ ducks
V $\rightarrow$ saw
Prn $\rightarrow$ she | her
Prp $\rightarrow$ in | with
Det $\rightarrow$ a | the

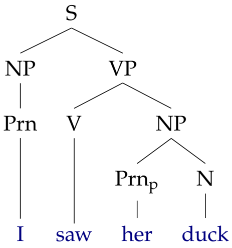
Derivation of sentence ‘she saw a duck’

S $\Rightarrow$ NP VP
NP $\Rightarrow$ Prn
Prn $\Rightarrow$ she
VP $\Rightarrow$ V NP
V $\Rightarrow$ saw
NP $\Rightarrow$ Det N
Det $\Rightarrow$ a
N $\Rightarrow$ duck



Representations of a context-free parse tree

A parse tree:



A history of derivations:

- S $\Rightarrow$ NP VP
- NP $\Rightarrow$ Prn
- Prn $\Rightarrow$ I
- VP $\Rightarrow$ V NP
- V $\Rightarrow$ saw
- NP $\Rightarrow$ Prn_p N
- Prn_p $\Rightarrow$ her
- N $\Rightarrow$ duck

A sequence with (labeled) brackets

$$\left[_{\text{S}} \left[_{\text{NP}} [_{\text{Prn}}\ \text{I}] \right] \left[_{\text{VP}} [_{\text{V}}\ \text{saw}]\ [_{\text{NP}}\ [_{\text{Prn}_\text{p}}\ \text{her}]\ [_{\text{N}}\ \text{duck}]\ ] \right] \right]$$

Parsing with context-free grammars

- Parsing can be
  - top down: start from S, search for derivation that leads to the input
  - bottom up: start from input, try to *reduce* it to S
- Naive search for both recognition/parse is intractable
- Dynamic programming methods allow polynomial time *recognition*

CKY bottom-up, requires Chomsky normal form

Earely top-down (with bottom-up filtering), works with unrestricted grammars

  - $O(n^3)$ time complexity (for recognition)
- Chart parsers are (reasonably) efficient, and they can represent ambiguity in their output
- However, they do not help with *resolving ambiguity*

Natural languages are ambiguous

Some types of ambiguities

- Lexical ambiguity
  - She is looking for a match
  - We saw her duck
- Attachment ambiguity
  - I saw the man with a telescope
  - Panda eats bamboo shoots and leaves
- Local ambiguity (garden path sentences)
  - The horse raced past the barn fell
  - The old man the boats
  - Fat people eat accumulates

Ambiguity and the parsers

- Given a grammar, chart parsers (e.g., CKY, Early) can parse natural language sentences relatively efficiently
- These parsers also represent all possible parse trees in their chart/output efficiently
- However, they have nothing to say about which of these parses are the most likely one.
- The task of selecting the best parse among many is called disambiguation
- In almost all practical uses, parsers are combined with disambiguators

We do not recognize many ambiguities

- Time flies like an arrow
- Outside of a dog, a book is a man's best friend
- One morning I shot an elephant in my pajamas
- Don't eat the pizza with a knife and fork

A parser, nevertheless, produces multiple parses for these sentences.

We do not recognize many ambiguities

- Time flies like an arrow; fruit flies like a banana
- Outside of a dog, a book is a man's best friend
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A parser, nevertheless, produces multiple parses for these sentences.

We do not recognize many ambiguities

- Time flies like an arrow; fruit flies like a banana
- Outside of a dog, a book is a man's best friend; inside it's too hard to read
- One morning I shot an elephant in my pajamas
- Don't eat the pizza with a knife and fork

A parser, nevertheless, produces multiple parses for these sentences.

We do not recognize many ambiguities

- Time flies like an arrow; fruit flies like a banana
- Outside of a dog, a book is a man's best friend; inside it's too hard to read
- One morning I shot an elephant in my pajamas. How he got in my pajamas, I don't know.
- Don't eat the pizza with a knife and fork

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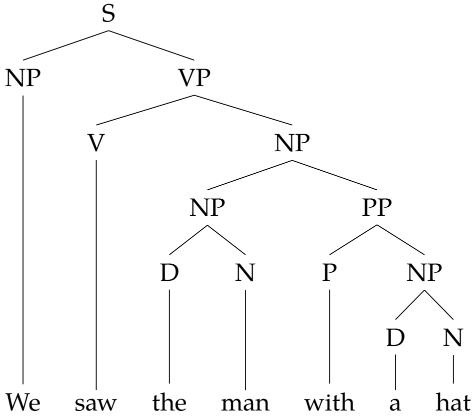
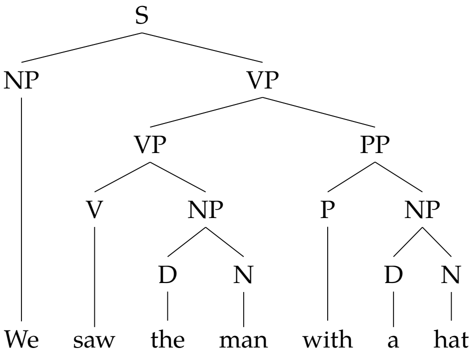
We do not recognize many ambiguities

- Time flies like an arrow; fruit flies like a banana
- Outside of a dog, a book is a man's best friend; inside it's too hard to read
- One morning I shot an elephant in my pajamas. How he got in my pajamas, I don't know.
- Don't eat the pizza with a knife and fork; the one with mushrooms is better.

A parser, nevertheless, produces multiple parses for these sentences.

The task: choosing the most plausible parse





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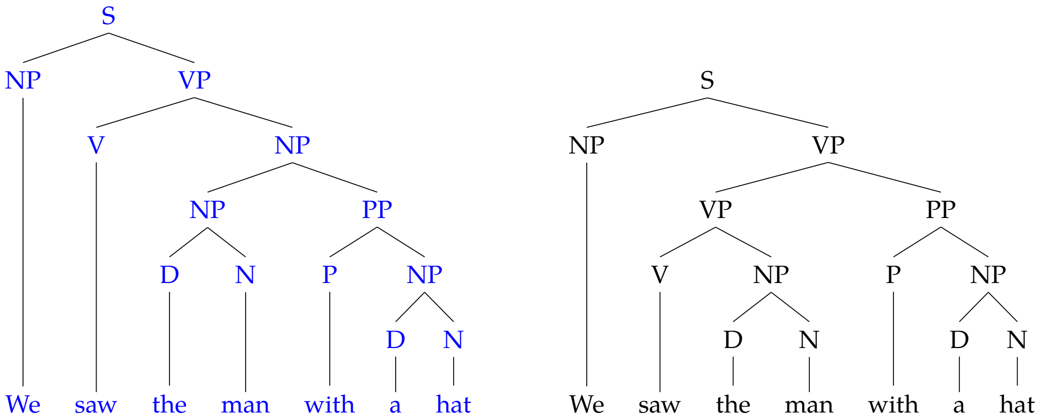


Statistical parsing

- Find the most plausible parse of an input string given all possible parses
- We need a scoring function, for each parse, given the input
- We typically use probabilities for scoring, task becomes finding the parse (or tree), t, given the input string $\boldsymbol{w}$

$$t_{\text{best}} = \arg\max_{t} P(t \mid \boldsymbol{w})$$

- Note that some ambiguities need a larger context than the sentence to be resolved correctly

Probability refresher (1)

- Probability is a measure of (un)certainty of an event
- We quantify the probability of an event with a number between 0 and 1
  - 0 the event is impossible
  - 0.5 the event is as likely to happen (or happened) as it is not
  - 1 the event is certain
- All possible outcomes of a trial (experiment or observation) is called the *sample space* (Ω)

Axioms of probability states that

1. $P(E) \in \mathbb{R}, P(E) \geqslant 0$
2. $P(\Omega) = 1$
3. For *disjoint* events E_1 and E_2, $P(E_1 \cup E_2) = P(E_1) + P(E_2)$

Probability refresher (2)

Joint and conditional probabilities, chain rule

- Joint probability of two events is noted as $P(x, y)$
- The conditional probability is defined as
  $$P(x|y) = \frac{P(x,y)}{P(y)} \text{ or } P(x, y) = P(x|y)P(y)$$
- If the events x and y are independent,
  $$P(x|y) = P(x),\ P(y|x) = p(y),\ P(x, y) = P(x)P(y)$$
- For more than two variables (chain rule):
  $$P(x, y, z) = P(z|x, y)P(y|x)P(x) = P(x|y, z)P(y|z)P(z) = \ldots$$
- If all are independent
  $$P(x, y, z) = P(x)P(y)P(z)$$

Probabilistic context free grammars (PCFG)

- A probabilistic context free grammar augments a CFG by adding a probability value to each rule

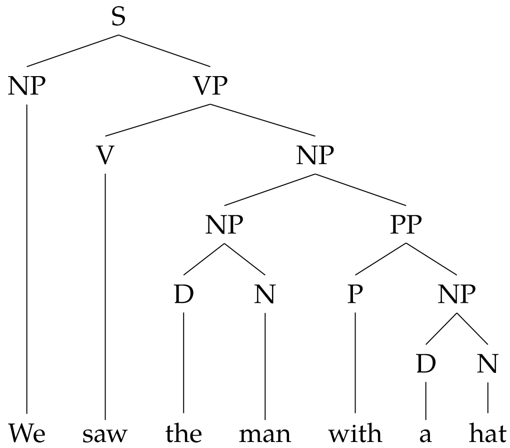
$$A \rightarrow \alpha \quad [p]$$

  where A is a non-terminal, α is string of terminals and non-terminals, and p *is the probability associated with the rule*
- Like CFGs, a PCFG accepts a sentence if it can be derived from S with rules $R_1 \ldots R_k$
- *The probability of a parse tree* t *of input string* $\boldsymbol{w}$, $P(t \mid \boldsymbol{w})$, *corresponding to the derivation* $R_1 \ldots R_k$ *is*

$$P(t \mid \boldsymbol{w}) = \prod_1^k p(R_i)$$

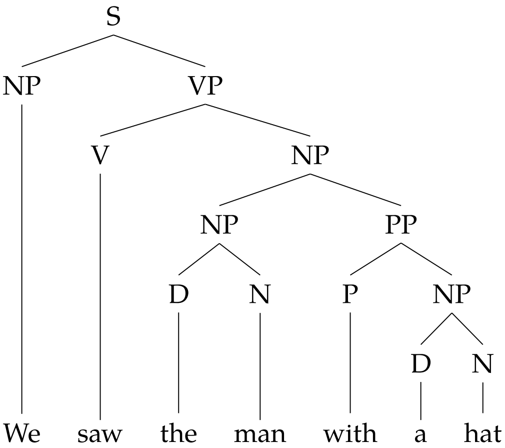
  where $p(R_i)$ *is the probability of the rule* R_i

PCFG example (1)



S	→	NP VP	1.0
NP	→	D N	0.7
NP	→	NP PP	0.2
NP	→	We	0.1
VP	→	V NP	0.9
VP	→	VP PP	0.1
PP	→	P NP	1.0
N	→	hat	0.2
N	→	man	0.8
V	→	saw	1.0
P	→	with	1.0
D	→	a	0.6
D	→	the	0.4

PCFG example (1)



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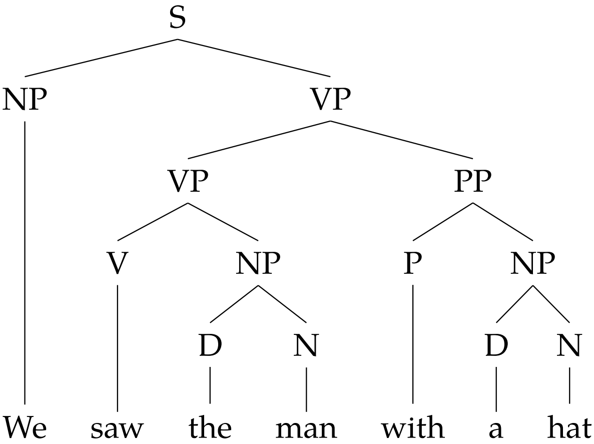
N	$\rightarrow$	hat	0.2
N	$\rightarrow$	man	0.8
V	$\rightarrow$	saw	1.0
P	$\rightarrow$	with	1.0
D	$\rightarrow$	a	0.6
D	$\rightarrow$	the	0.4

$$\begin{aligned} P(t) &= 1.0 \times 0.1 \times 0.9 \times 1.0 \times 0.2 \times 0.7 \times 0.4 \times 0.8 \times 1.0 \times 1.0 \times 0.7 \times 0.6 \times 0.2 \\ &= 0.000263424 \end{aligned}$$

PCFG example (2)



S	$\rightarrow$	NP VP	1.0
NP	$\rightarrow$	D N	0.7
NP	$\rightarrow$	NP PP	0.2
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D	$\rightarrow$	a	0.6
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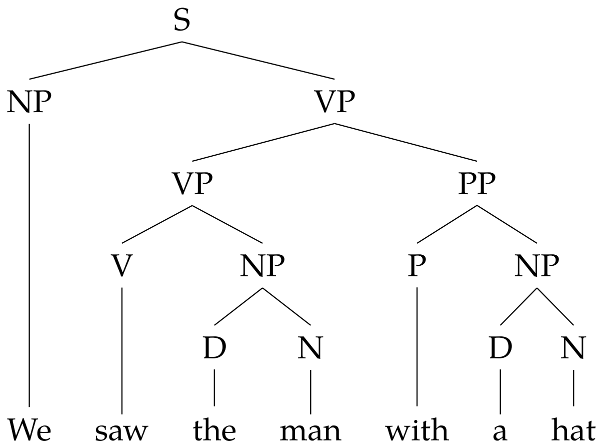
PCFG example (2)



S	$\rightarrow$	NP VP	1.0
NP	$\rightarrow$	D N	0.7
NP	$\rightarrow$	NP PP	0.2
NP	$\rightarrow$	We	0.1
VP	$\rightarrow$	V NP	0.9
VP	$\rightarrow$	VP PP	0.1
PP	$\rightarrow$	P NP	1.0
N	$\rightarrow$	hat	0.2
N	$\rightarrow$	man	0.8
V	$\rightarrow$	saw	1.0
P	$\rightarrow$	with	1.0
D	$\rightarrow$	a	0.6
D	$\rightarrow$	the	0.4

$$
\begin{aligned}
P(t) &= 1.0 \times 0.1 \times 0.1 \times 0.9 \times 1.0 \times 0.7 \times 0.4 \times 0.8 \times 1.0 \times 1.0 \times 0.7 \times 0.6 \times 0.2 \\
&= 0.0001693440
\end{aligned}
$$

Where do the rule probabilities come from?

- Supervised: estimate from a treebank, e.g., using maximum likelihood estimation
- Unsupervised: expectation-maximization (EM)

PCFGs - an interim summary

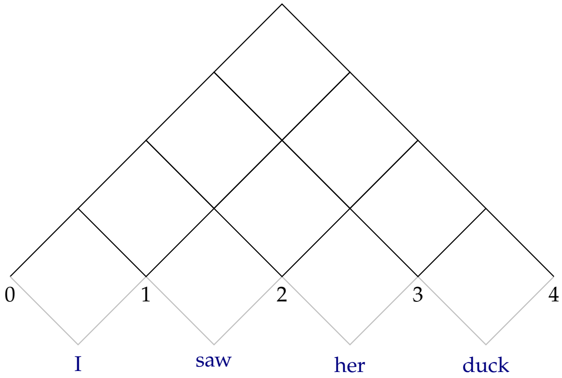
- PCFGs assign probabilities to parses based on CFG rules used during the parse
- PCFGs assume that the rules are independent
- PCFGs are generative models, they assign probabilities to $P(t, \boldsymbol{w})$, we can calcuate the probability of a sentence by

$$P(\boldsymbol{w}) = \sum_{t} P(t, \boldsymbol{w}) = \sum_{t} P(t)$$

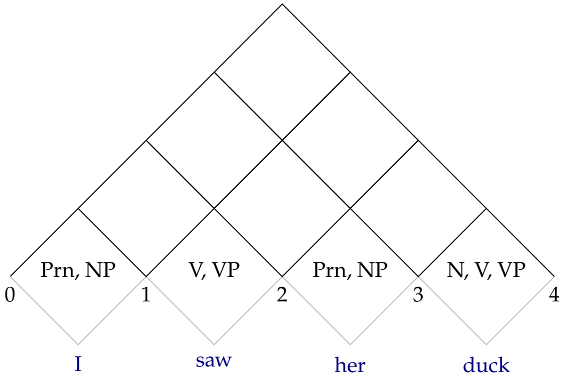
PCFG chart parsing

- Both CKY and Earley algorithms can be adapted to PCFG parsing
- CKY matches PCFG parsing quite well
  - to get the best parse, store the constituent with the highest probability in every cell of the chart
  - to get n-best best parse (beam search), store the n-best constituents in every cell in the chart

CKY for PCFG parsing



CKY for PCFG parsing



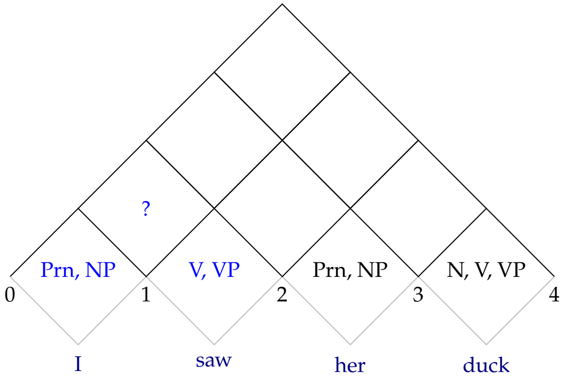
$P(Prn_{01}) = P(Prn \rightarrow I)$ $P(NP_{01}) = P(NP \rightarrow I)$

$P(V_{12}) = P(V \rightarrow saw)$ $P(VP_{12}) = P(VP \rightarrow saw)$

...

CKY for PCFG parsing

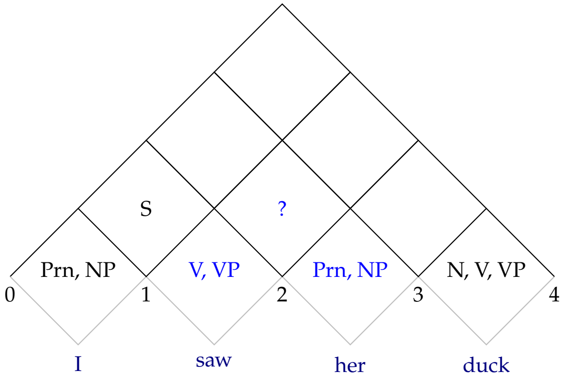
$$S \rightarrow NP\ VP$$



$$P(S_{02} \Rightarrow NP_{01} VP_{12}) = P(NP_{01})P(VP_{12})P(S \rightarrow NP\ VP)$$

CKY for PCFG parsing

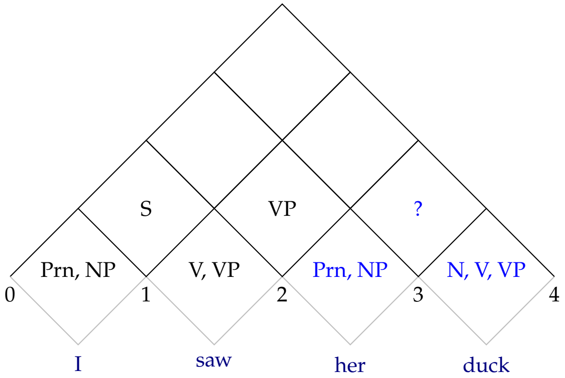
$$VP \rightarrow V\ NP$$



$$P(VP_{13} \Rightarrow V_{12}NP_{23}) = P(V_{12})P(NP_{23})P(VP \rightarrow V\ NP)$$

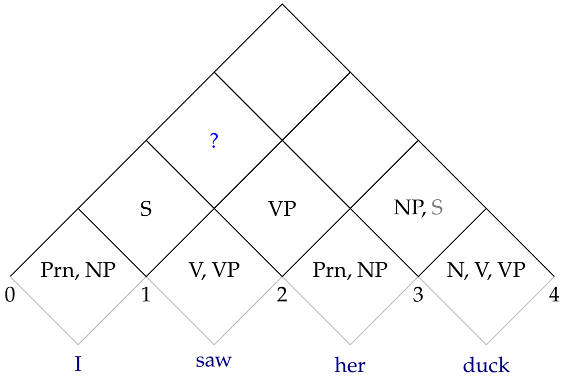
CKY for PCFG parsing

$$
\begin{aligned}
NP &\rightarrow Prn\ N \\
S &\rightarrow NP\ VP
\end{aligned}
$$



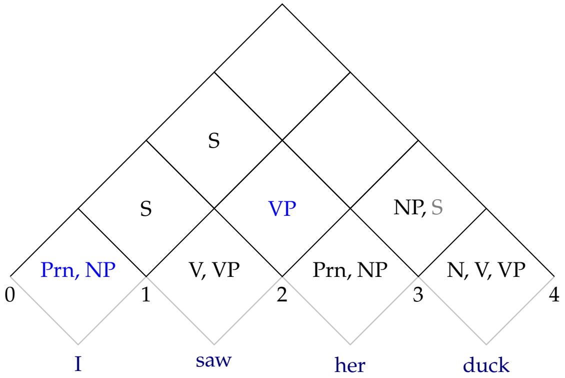
$$P(NP_{24} \Rightarrow Prn_{23}N_{34}) = P(Prn_{23})P(N_{34})P(NP \rightarrow Prn\ N)$$
$$>$$
$$P(S_{24} \Rightarrow NP_{23}VP_{34}) = P(NP_{23})P(VP_{34})P(S \rightarrow NP\ VP)$$

CKY for PCFG parsing



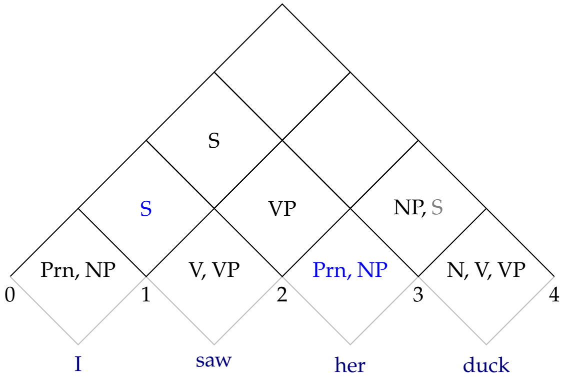
CKY for PCFG parsing

$S \rightarrow NP\ VP$

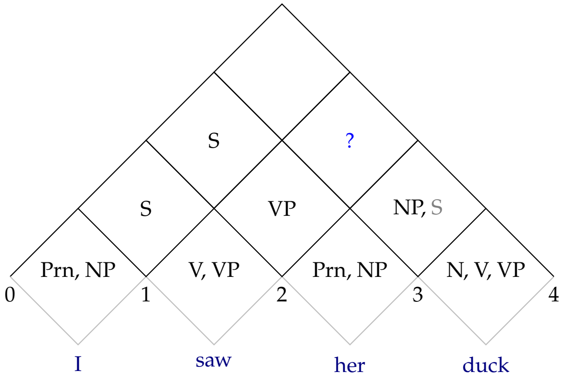


$$P(S_{03} \Rightarrow NP_{01} VP_{23}) = P(NP_{01}) P(VP_{13}) P(S \rightarrow NP\ VP)$$

CKY for PCFG parsing

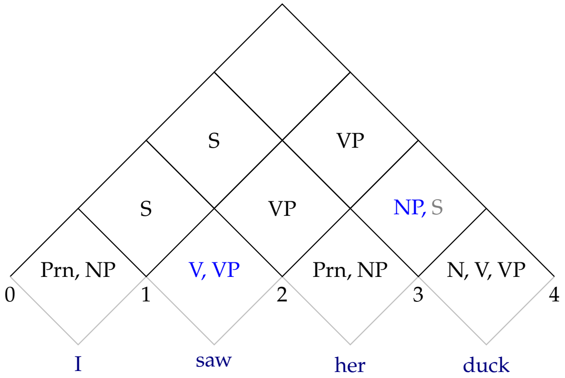


CKY for PCFG parsing



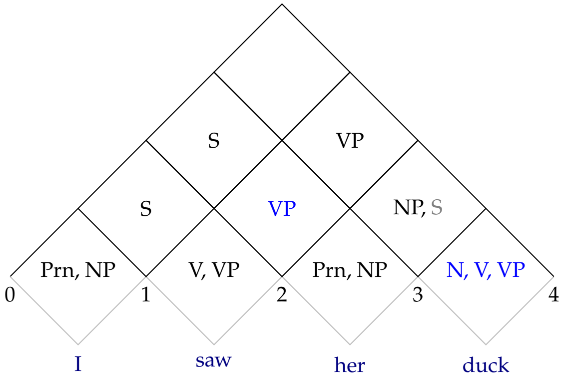
CKY for PCFG parsing

$$\text{VP} \rightarrow \text{V NP}$$
$$\text{VP} \rightarrow \text{V S}$$

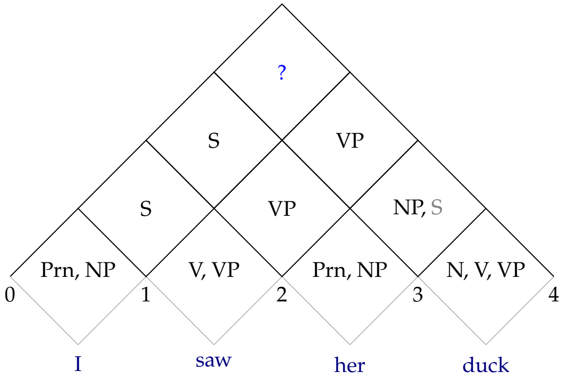


$$P(\text{VP}_{14} \Rightarrow \text{V}_{12}\text{NP}_{24}) = P(\text{V}_{12})P(\text{NP}_{24})P(\text{VP} \rightarrow \text{V NP})$$

CKY for PCFG parsing

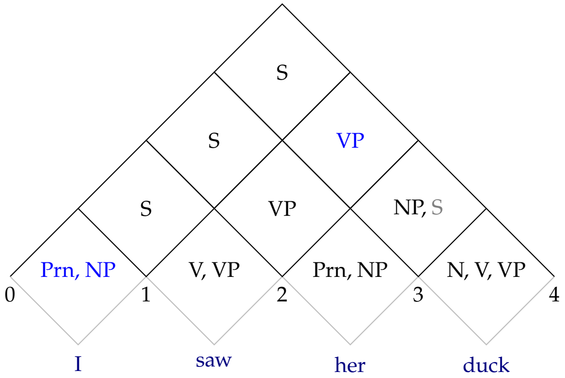


CKY for PCFG parsing



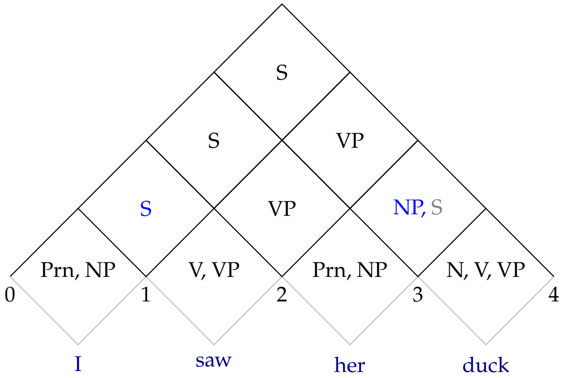
CKY for PCFG parsing

$$S \rightarrow NP\ VP$$



$$P(S_{14} \Rightarrow NP_{01}VP_{14}) = P(NP_{01})P(VP_{14})P(S \rightarrow NP\ VP)$$

CKY for PCFG parsing



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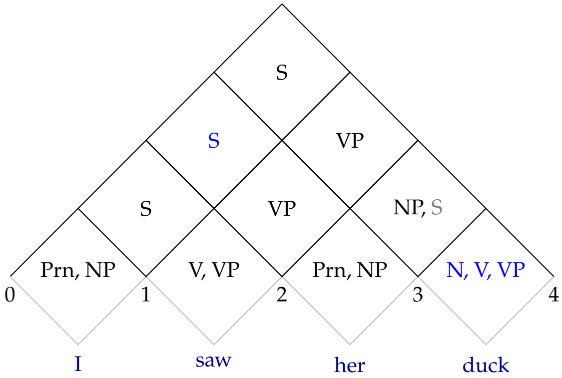

What makes the difference in PCFG probabilities?

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NP	$\Rightarrow$	We	0.1
VP	$\Rightarrow$	VP PP	0.1
VP	$\Rightarrow$	V NP	0.8
V	$\Rightarrow$	saw	1.0
NP	$\Rightarrow$	D N	0.7
D	$\Rightarrow$	the	0.4
N	$\Rightarrow$	man	0.8
PP	$\Rightarrow$	P NP	1.0
P	$\Rightarrow$	with	1.0
NP	$\Rightarrow$	D N	0.7
D	$\Rightarrow$	a	0.6
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The parser's choice would not be affected by lexical items!

What is wrong with PCFGs?

- In general: the assumption of independence
- The parents affect the correct choice for children, for example, in English NP $\rightarrow$ Prn is more likely in the subject position
- The lexical units affect the correct decision, for example:
  - We eat the pizza with hands
  - We eat the pizza with mushrooms
- Additionally: PCFGs use local context, difficult to incorporate arbitrary/global features for disambiguation

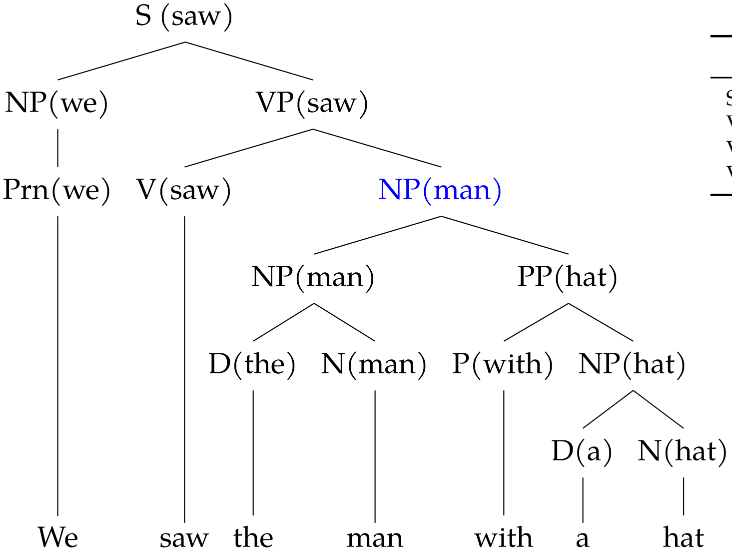
Solutions to PCFG problems

- Independence assumptions can be relaxed by either
  - Parent annotation
  - Lexicalization
  - Reranking
- To condition on arbitrary/global information: discriminative models
- Most practical PCFG parsers are lexicalized, and often use a re-ranker conditioning on other (global) features

Lexicalizing PCFGs

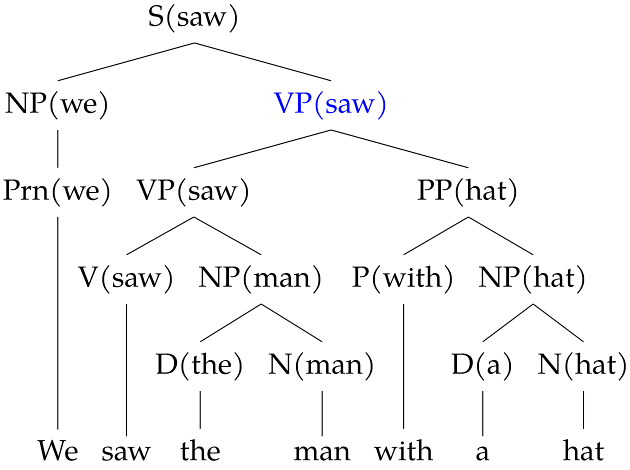
- Replace non-terminal X with $X(h)$, where h is a tuple with the lexical word and its POS tag
- Now the grammar can capture (head-driven) lexical dependencies
- But number of nonterminals grow by $|V| \times |T|$
- Estimation becomes difficult (many rules, data sparsity)
- Some treebanks (e.g., Penn Treebank) do not annotate heads, they are automatically annotated (based on heuristics)

Example lexicalized derivation



Example rules:		
S(saw)	$\rightarrow$	NP(we) VP(saw)
VP(saw)	$\rightarrow$	V(saw) NP(man)
VP(saw)	$\rightarrow$	VP(saw) PP(hat)
VP(saw)	$\rightarrow$	VP(saw) PP(telescope)

Example lexicalized derivation



Example rules:		
S(saw)	$\rightarrow$	NP(we) VP(saw)
VP(saw)	$\rightarrow$	V(saw) NP(man)
VP(saw)	$\rightarrow$	VP(saw) PP(hat)
VP(saw)	$\rightarrow$	VP(saw) PP(telescope)

Evaluating the parser output

- A parser can be evaluated

  extrinsically — based on its effect on a task (e.g., machine translation) where it is used

  intrinsically — based on the match with ideal parsing
- The typically evaluation (intrinsic) is based on a *gold standard* (GS)
- Exact match is often
  - very difficult to achieve (think about a 50-word newspaper sentence)
  - not strictly necessary (recovering parts of the parse can be useful for many purposes)

Parser evaluation metrics

- Common evaluation metrics are (PARSEVAL):

  precision the ratio of correctly predicted nodes

  recall the nodes (in GS) that are predicted correctly

  f-measure harmonic mean of precision and recall $\left(\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}\right)$

- The measures can be

  unlabled the spans of the nodes are expected to match

  labeled the node label should also match

- Crossing brackets (or average non-crossing brackets)

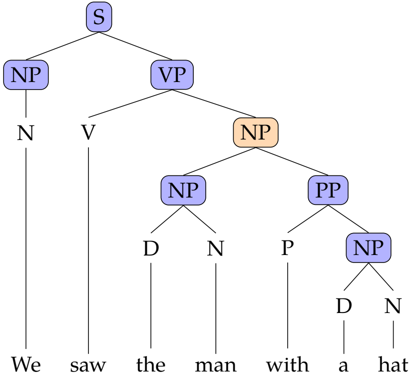
  (We (saw (them (with binoculars))))

  (We ((saw them) (with binoculars)))

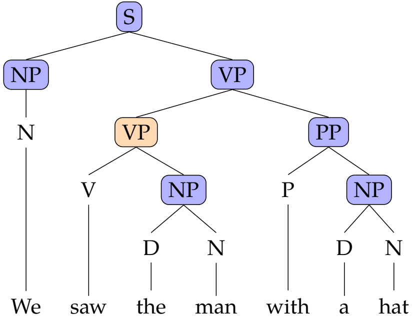
- Measures can be averaged per constituent (micro average), or over sentences (macro average)

PARSEVAL example

Gold standard:



Parser output:



$$\text{precision} = \frac{6}{7} \quad \text{recall} = \frac{6}{7} \quad \text{f-measure} = \frac{6}{7}$$

Problems with PARSEVAL metrics

- PARSEVAL metrics favor certain type of structures
  - Results are surprisingly well for flat tree structures (e.g., Penn treebank)
  - Results of some mistakes are catastrophic (e.g., low attachment)
- Not all mistakes are equally important for semantic distinctions
- Some alternatives:
  - Extrinsic evaluation
  - Evaluation based on extracted dependencies

Summary

- PCFG is a simple attempt to augment CFG with probabilities
- PCFG parsing alone is suboptimal: independence assumptions are too strong
- Solutions include (a combination of) lexicalization, parent annotation and re-ranking
- Reading suggestion: **jurafsky2009**

Summary

- PCFG is a simple attempt to augment CFG with probabilities
- PCFG parsing alone is suboptimal: independence assumptions are too strong
- Solutions include (a combination of) lexicalization, parent annotation and re-ranking
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Next:

- Dependency grammars and dependency parsing

Acknowledgments, references, additional reading material

Aho, Alfred V., Monica S. Lam, Ravi Sethi, and Jeffrey D. Ullman (2007). *Compilers: Principles, Techniques, & Tools*. Pearson/Addison Wesley. ISBN: 9780321486813.

Grune, Dick and Ceriel J.H. Jacobs (2007). *Parsing Techniques: A Practical Guide*. second. Monographs in Computer Science. The first edition is available at `http://dickgrune.com/Books/PTAPG_1st_Edition/BookBody.pdf`. Springer New York. ISBN: 9780387689548.