# Probabilistic context-free parsing

Parsing
ISCL-BA-06

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## 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 $\alpha$ is a (possibly empty) sequence of terminal or non-terminal symbols



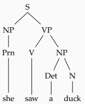


## An example context-free grammar

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

Derivation of sentence 'she saw a duck'

S ⇒ NP VP
NP ⇒ Prn
Prn ⇒ she
VP ⇒ V NP
V ⇒ saw
NP ⇒ Det N
Det ⇒ a
N ⇒ duck

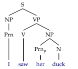







## Representations of a context-free parse tree

*A parse tree:*




*A history of derivations:*

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

*A sequence with (labeled) brackets*

$\left[_S \left[_{NP} [_{Prn}\ I]\right] \left[_{VP} [_V\ saw]\ [_{NP} [_{Prn_p}\ her]\ [_N\ duck]]\right]\right]$





## 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

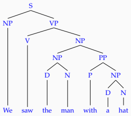
- Time flies like an arrow; fruit flies like a banana
- Outside of a dog, a book is a man's best friend; inside it's too hard to read
- One morning I shot an elephant in my pajamas. How he got in my pajamas, I don't know.
- Don't eat the pizza with a knife and fork; the one with mushrooms is better.

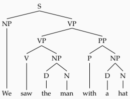
A parser, nevertheless, produces multiple parses for these sentences.





## The task: choosing the most plausible parse








## 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 $\boldsymbol{w}$

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

- 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* ($\Omega$)

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
  $$P(x, y, z) = P(x)P(y)P(z)$$





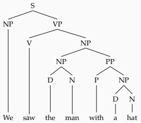
## Probabilistic context free grammars (PCFG)

- 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, $\alpha$ 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)



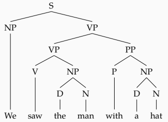

| | | |
|---|---|---|
| S | → NP VP | 1.0 |
| NP | → D N | 0.7 |
| NP | → NP PP | 0.2 |
| NP | → We | 0.1 |
| VP | → V NP | 0.9 |
| VP | → VP PP | 0.1 |
| PP | → P NP | 1.0 |
| N | → hat | 0.2 |
| N | → man | 0.8 |
| V | → saw | 1.0 |
| P | → with | 1.0 |
| D | → a | 0.6 |
| D | → the | 0.4 |

$P(t) = 1.0 \times 0.1 \times 0.9 \times 1.0 \times 0.2 \times 0.7 \times 0.4 \times 0.8 \times 1.0 \times 1.0 \times 0.7 \times 0.6 \times 0.2$
$= 0.000263424$





## PCFG example (2)




| | | |
|---|---|---|
| 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 |

$P(t) = 1.0 \times 0.1 \times 0.1 \times 0.9 \times 1.0 \times 0.7 \times 0.4 \times 0.8 \times 1.0 \times 1.0 \times 0.7 \times 0.6 \times 0.2$
$= 0.0001693440$





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





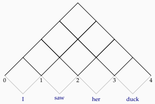
## PCFG chart parsing

- 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





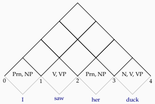
## CKY for PCFG parsing








## CKY for PCFG parsing



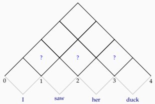

$P(Prn_{01}) = P(Prn \rightarrow I)$ $\quad P(NP_{01}) = P(NP \rightarrow I)$
$P(V_{12}) = P(V \rightarrow saw)$ $\quad P(VP_{12}) = P(VP \rightarrow saw)$
...





## CKY for PCFG parsing

S → NP VP



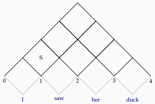

$P(S_{02} \Rightarrow NP_{01}VP_{12}) = P(NP_{01})P(VP_{12})P(S \rightarrow NP\ VP)$





## CKY for PCFG parsing

VP → V NP



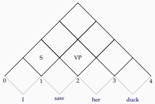

$P(VP_{13} \Rightarrow V_{12}NP_{23}) = P(V_{12})P(NP_{23})P(VP \rightarrow V\ NP)$





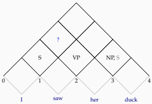
## CKY for PCFG parsing

NP → Prn N
S → NP VP




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

## CKY for PCFG parsing

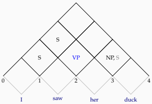







## CKY for PCFG parsing

S → NP VP

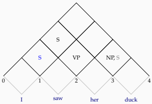



$P(S_{03} \Rightarrow NP_{01}VP_{23}) = P(NP_{01})P(VP_{13})P(S \rightarrow NP\ VP)$





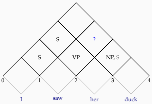
## CKY for PCFG parsing








## CKY for PCFG parsing

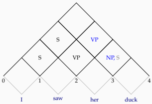







## CKY for PCFG parsing

VP → V NP
VP → V S

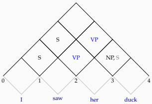



$P(VP_{14} \Rightarrow V_{12}NP_{24}) = P(V_{12})P(NP_{24})P(VP \rightarrow V\ NP)$





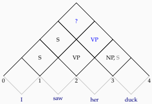
## CKY for PCFG parsing








## CKY for PCFG parsing

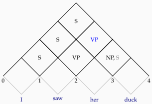







## CKY for PCFG parsing

S → NP VP

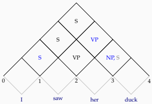



$P(S_{14} \Rightarrow NP_{01}VP_{14}) = P(NP_{01})P(VP_{14})P(S \rightarrow NP\ VP)$





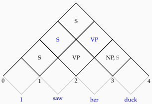
## CKY for PCFG parsing








## CKY for PCFG parsing








## What makes the difference in PCFG probabilities?

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

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 → 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





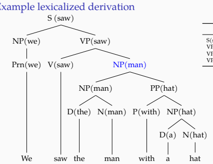
## Lexicalizing PCFGs

- 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

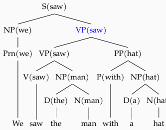



| Example rules: | |
|---|---|
| S(saw) | → NP(we) VP(saw) |
| VP(saw) | → V(saw) NP(man) |
| VP(saw) | → VP(saw) PP(hat) |
| VP(saw) | → VP(saw) PP(telescope) |





## Example lexicalized derivation

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| VP(saw) | → V(saw) NP(man) |
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| VP(saw) | → 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

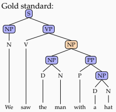
- Common evaluation metrics are (PARSEVAL):
  - precision: the ratio of correctly predicted nodes
  - recall: the nodes (in GS) that are predicted correctly
  - f-measure: harmonic mean of precision and recall $\left(\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}\right)$
- 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)



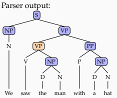


## PARSEVAL example

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: Jurafsky and Martin (2009, Chapter 14)

Next:

- Dependency grammars and dependency parsing



## Acknowledgments, references, additional reading material

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.

Jurafsky, Daniel and James H. Martin (2009). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition.* second. Pearson Prentice Hall. ISBN: 978-0-13-504196-3. URL: `http://web.stanford.edu/~jurafsky/slp3/`.