Foundations for Natural Language Processing

Syntax and Parsing

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(with slides from Ivan Titov, Alex Lascarides, Sharon Goldwater, Mark Steedman, and Marco Kuhlmann)

School of informatics

Today

- Last few words about sequence modeling
- Basics of Syntax, Context-Free Grammars
- Classes of Syntactic Parsing Algorithms
- Start with the CKY algorithm

Recap: Sequence labeling problems

- Definition:
  - Input: sequences of variable length $\mathbf{x} = (x_1, x_2, \ldots, x_{|x|}), x_i \in \mathcal{X}$
  - Output: every position is associated with a label $\mathbf{y} = (y_1, y_2, \ldots, y_{|x|}), y_i \in \{1, \ldots, N\}$
- An example:
  - Part-of-speech tagging

$\mathbf{x} =$	**John**	**carried**	**a**	**tin**	**can**	**.**
$\mathbf{y} =$	NNP	VBD	DT	NN	NN	.

Back to generative modeling – HMMs, what else?

- Using Viterbi, we can find the best tags for a sentence (decoding), and get $P(y, x|\theta)$ with HMM
  - or $P(\mathbf{y} \mid \mathbf{x})$ if you use the conditional modeling
- We might also want to
  - compute the likelihood, i.e., the probability of a sentence regardless of its tags (a language model!) $P(x|\theta)$
  - learn the best set of parameters $\hat{\theta}$ given only an unannotated corpus of sentences.

Computing the likelihood

- From the probability theory we know

$$P(x|\theta) = \sum_y P(x, y|\theta)$$

- But there are an exponential number of sequences *y*
- Again, by computing and storing partial results, we can solve efficiently.

Viterbi

Initialization: $v_j^1 = a_{START,j} b_{j,x^1}, \quad j = 1, \ldots, N;$

Recomputation: $v_j^t = \left(\max_i v_i^{t-1} a_{ij} \right) b_{j,x^t}, \; j = 1, \ldots, N, \; t = 2, \ldots, |x|$

Final: $v_{STOP}^{|\mathbf{x}|+1} = \max_i v_i^{|\mathbf{x}|} a_{i,STOP}$

Forward algorithm

Initialization: $v_j^1 = a_{START,j} b_{j,x^1}, \quad j = 1, \ldots, N;$

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$$P(\mathbf{y} \mid \mathbf{x}) = \frac{\exp\left(\sum_{t=1}^{|\mathbf{x}|} g^t(\mathbf{x}, y_{t-1}, y_t)\right)}{\sum_{\mathbf{y}'} \exp\left(\sum_{t=1}^{|\mathbf{x}|} g^t(\mathbf{x}, y'_{t-1}, y'_t)\right)}$$

This is also the algorithm used to compute the denominator for Markov Random Field, we considered last time

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Modelling word behaviour

- We've seen various ways to model word behaviour.
  - Bag-of-words models: ignore word order entirely
  - N-gram models: capture a fixed-length history to predict word sequences.
  - HMMs: also capture fixed-length history, using latent variables.
  - RNNs/Transformers: few restrictions, reliance on flexibility neural networks
- We will see how provide linguistic priors into models

Long-range dependencies

- The form of one word often depends on (agrees with) another, even when arbitrarily long material intervenes.

  Sam/Dogs sleeps/sleep soundly
  Sam, who is my cousin, sleeps soundly
  Dogs often stay at my house and sleep soundly
  Sam, the man with red hair who is my cousin, sleeps soundly

- We want models that can capture these dependencies.

Phrasal categories

- We may also want to capture substitutability at the phrasal level.
  - POS categories indicate which words are *substitutable*. For example, substituting **adjectives**:

I saw a red cat
I saw a former cat
I saw a billowy cat

  - Phrasal categories indicate which phrases are substitutable. For example, substituting **noun phrase**:

Dogs sleep soundly
My next-door neighbours sleep soundly
Green ideas sleep soundly

This is one example of "**constituency test**"

Example constituency tests: coordination

- Only constituents (of the same type) can be **coordinated** using conjunction words like *and*, *or*, and *but*
- Pass the test:

Her friends from Peru went to the show.
Mary *and* her friends from Peru went to the show.

Should I go through the tunnel?
Should I go through the tunnel *and* over the bridge?

- Fail the test

We peeled the potatoes.
*We peeled the and washed the potatoes.

Example constituency tests: clefting

- Only a constituent can appear in the frame "____ *is/are who/what/where/when/why/how* …"
- Pass the test:

They put the boxes in the basement.
In the basement *is where* they put the boxes.

- Fail the test

They put the boxes in the basement.
*Put the boxes is what they did in the basement.

Theories of syntax

- A theory of syntax should explain which sentences are well-formed (grammatical) and which are not.
  - Note that well-formed is distinct from meaningful.
  - Famous example from Chomsky:

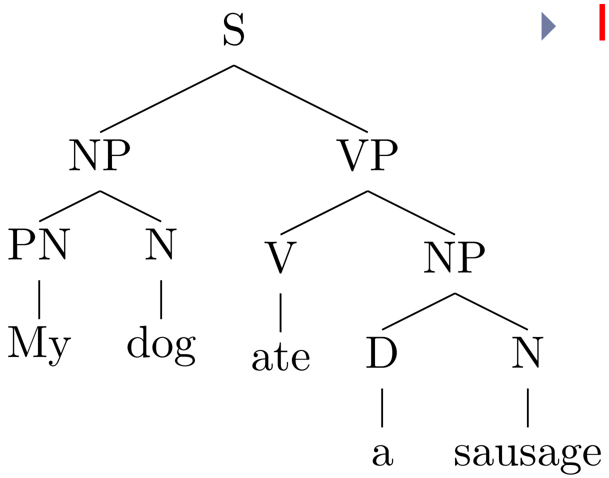
    Colorless green ideas sleep furiously
- (Even if the reason we care about syntax is mainly for interpreting meaning.)

Theories of syntax

- We'll look at one theory of syntax:
  - Constituency (aka phrase) structures

- A theory of syntax can be viewed as a model of language behaviour. As with other models, we will look at
  - What the model can capture, and what it cannot.
  - Algorithms that provide syntactic analyses for sentences using the model (i.e., syntactic parser).

Constituent trees



- Internal nodes correspond to phrases

  S – a sentence

  NP (Noun Phrase): My dog, a sandwich, lakes, ..

  VP (Verb Phrase): ate a sausage, barked, …

  PP (Prepositional phrases): with a friend, in a car, …

- Nodes immediately above words are PoS tags

  PN – pronoun
  D – determiner
  V – verb
  N – noun
  P – preposition

Context-Free Grammar

- Context-free grammar is a tuple of 4 elements $G = (V, \Sigma, R, S)$
  - V - the set of non-terminals
    In our case: phrase categories (VP, NP, ..) and PoS tags (N, V, .. – aka preterminals)
  - Σ - the set of terminals
    Words
  - R - the set of rules of the form $X \rightarrow Y_1, Y_2, \ldots, Y_n$, where $n \geq 0$, $X \in V,\ Y_i \in V \cup \Sigma$
    $$S \rightarrow NP\ \ VP$$
    $$NP \rightarrow D\ \ N$$
    $$NP \rightarrow PN$$
    $$NP \rightarrow NP\ \ PP$$
    $$PP \rightarrow P\ \ NP$$
    $$\ldots$$
    $$N \rightarrow girl$$
    $$N \rightarrow telescope$$
    $$V \rightarrow saw$$
    $$V \rightarrow eat$$
    $$\ldots$$
  - S is a dedicated start symbol

An example grammar

$$V = \{S, VP, NP, PP, N, V, PN, P\}$$

$$\Sigma = \{girl, telescope, sandwich, I, saw, ate, with, in, a, the\}$$

$$S = \{S\}$$

R :

Inner rules

$S \rightarrow NP \ \ VP$ (NP A girl) (VP ate a sandwich)

$VP \rightarrow V$

$VP \rightarrow V \ \ NP$ (V ate) (NP a sandwich)

$VP \rightarrow VP \ \ PP$ (VP saw a girl) (PP with a telescope)

$NP \rightarrow NP \ \ PP$ (NP a girl) (PP with a sandwich)

$NP \rightarrow D \ \ N$ (D a) (N sandwich)

$NP \rightarrow PN$

$PP \rightarrow P \ \ NP$ (P with) (NP with a sandwich)

Preterminal rules

$N \rightarrow girl$

$N \rightarrow telescope$

$N \rightarrow sandwich$

$PN \rightarrow I$

$V \rightarrow saw$

$V \rightarrow ate$

$P \rightarrow with$

$P \rightarrow in$

$D \rightarrow a$

$D \rightarrow the$

CFGs

S

$$\boxed{S \rightarrow NP\ \ VP}$$

$$VP \rightarrow V$$
$$VP \rightarrow V\ \ NP$$
$$VP \rightarrow VP\ \ PP$$

$$NP \rightarrow NP\ \ PP$$
$$NP \rightarrow D\ \ N$$
$$NP \rightarrow PN$$

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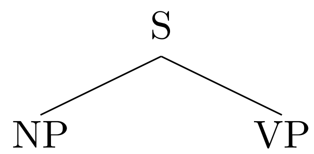

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$$NP \rightarrow D \;\; N$$

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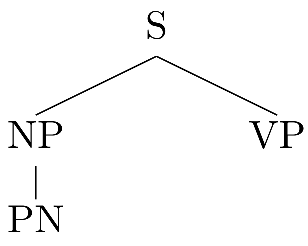

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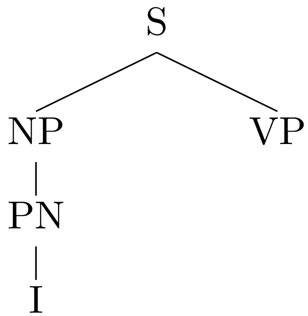

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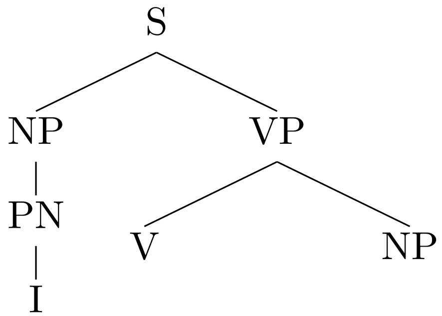

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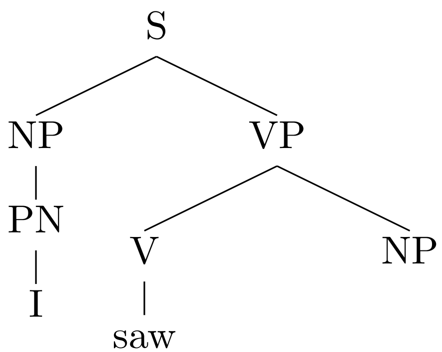

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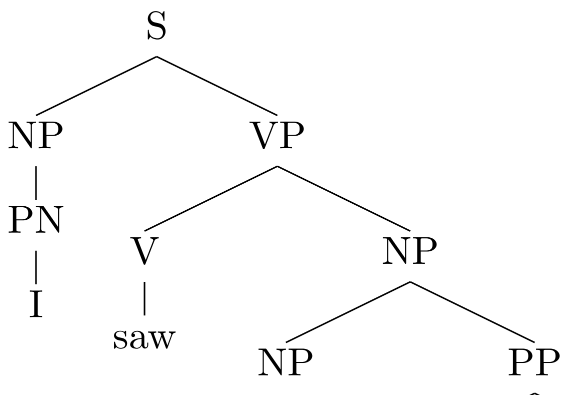

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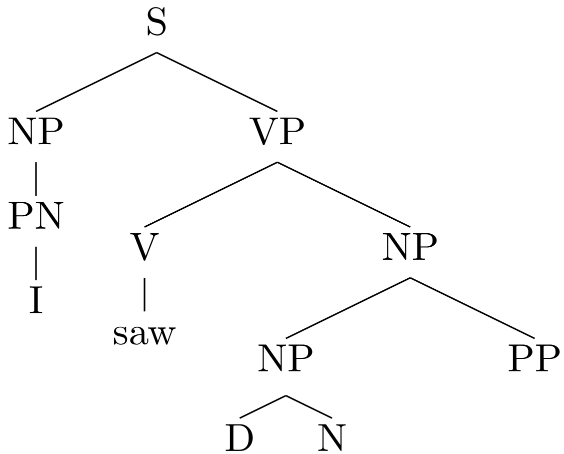

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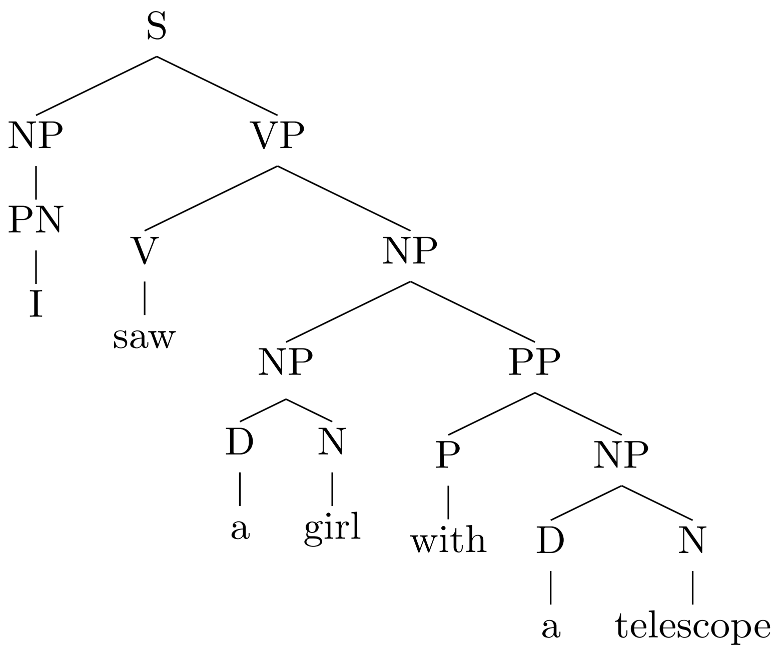
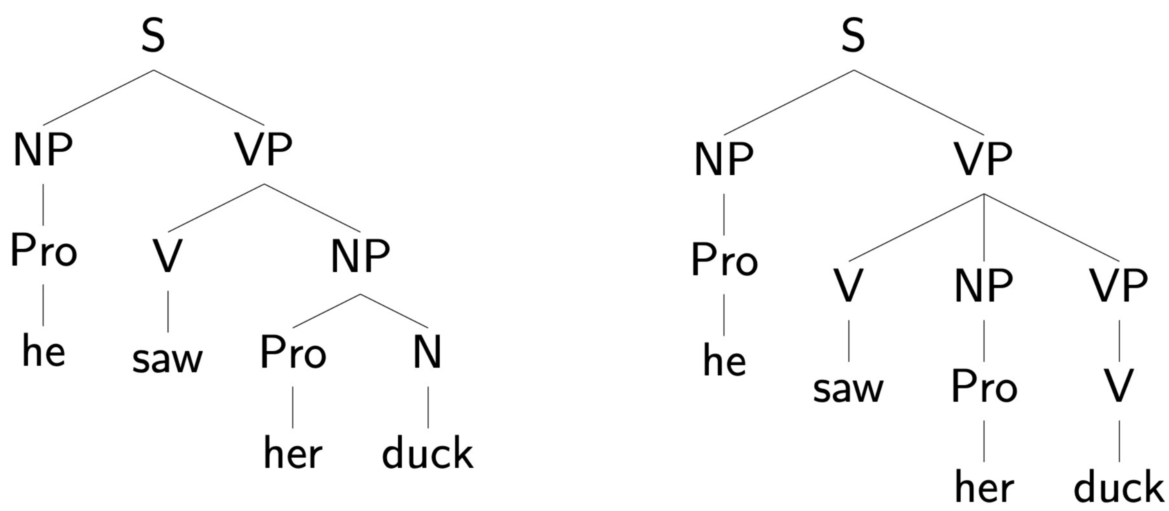


CFG defines both:

- a set of strings (a language)
- structures used to represent sentences (constituent trees)

Structural ambiguity

- Some sentences have more than one parse: structural ambiguity.



- Here, the structural ambiguity is caused by PoS ambiguity in several of the words. (Both are types of syntactic ambiguity.)

Structural ambiguity

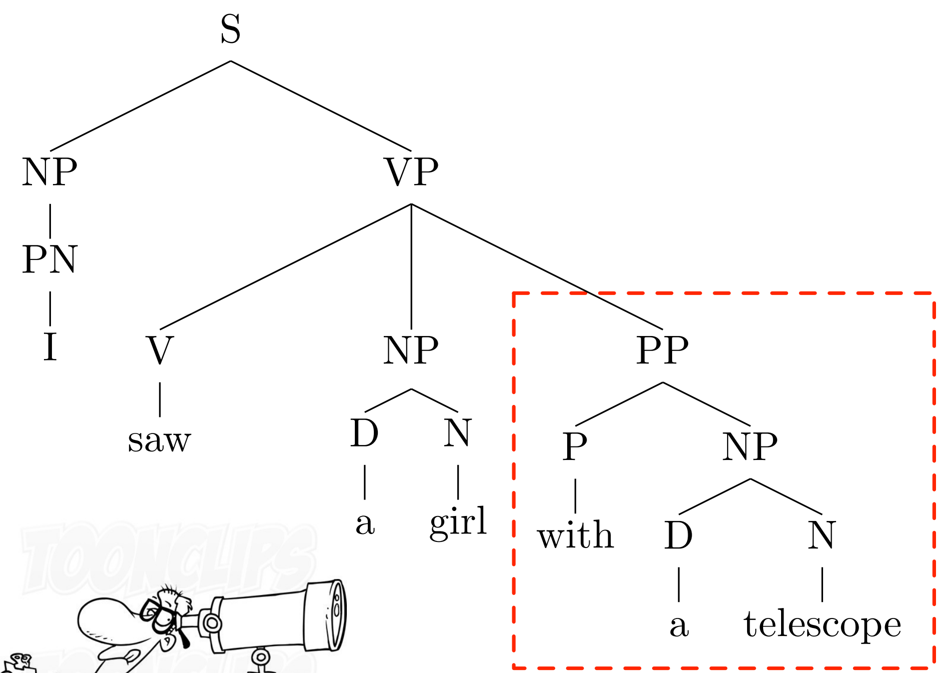
- Some sentences have structural ambiguity even **without** part-of-speech ambiguity. This is called attachment ambiguity.
  - Depends on where different phrases attach in the tree.
  - Different attachments have different meanings:

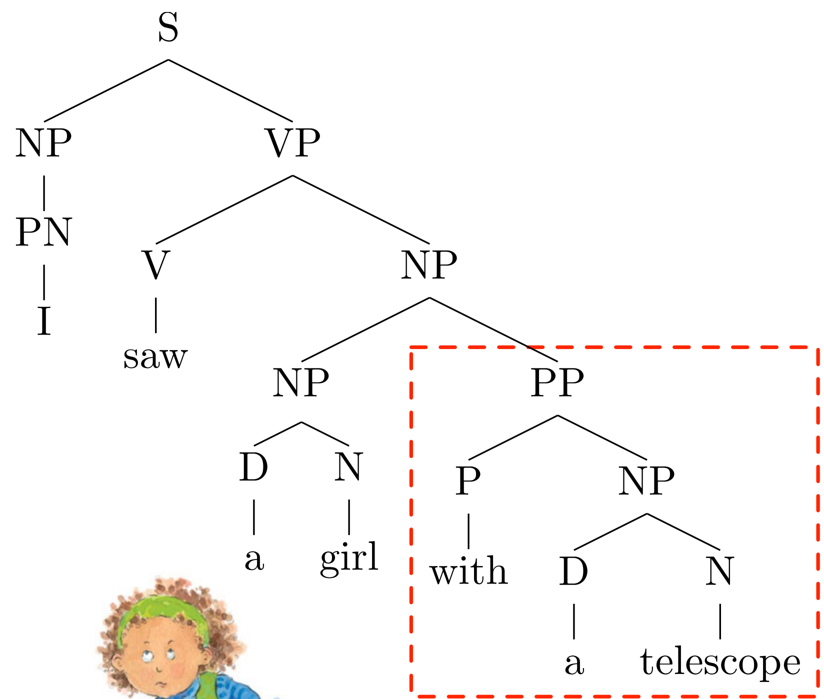
I saw a girl with a telescope
She ate the pizza on the floor
Good boys and girls get presents from Santa

- Next slide shows trees for the first example: prepositional phrase (PP) attachment ambiguity.

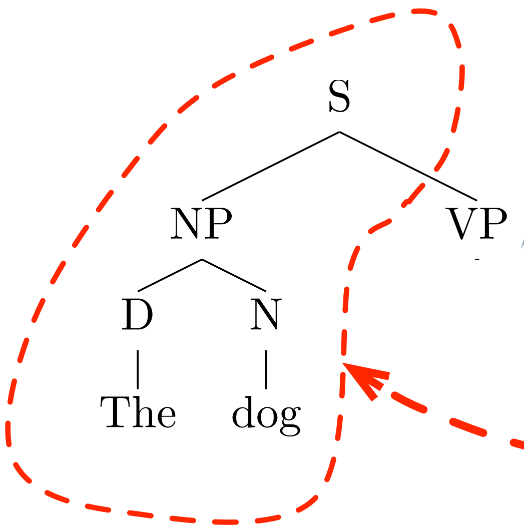
Prepositional Phrase (PP-) Attachment Ambiguity

- Prepositional phrase attachment ambiguity



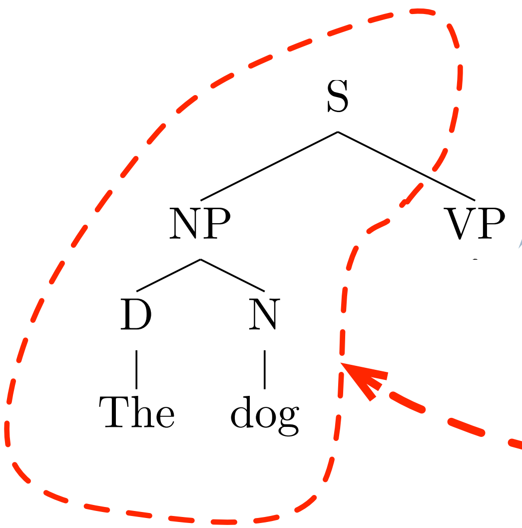


Why context-free?



What can be a sub-tree is only affected by what the phrase type is (VP) but not the context

Why context-free?



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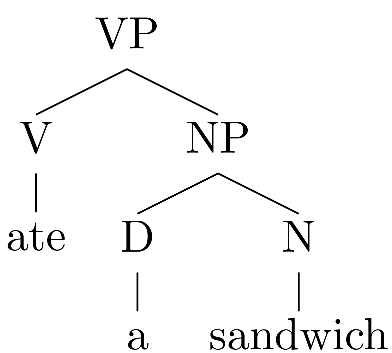
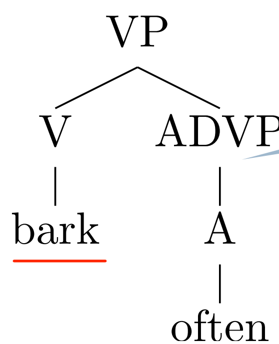
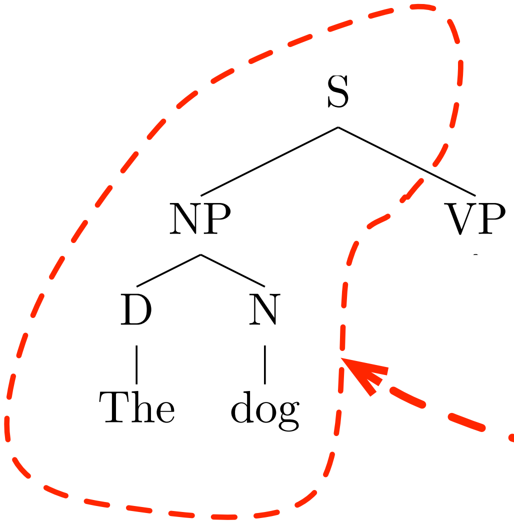




Not grammatical

Why context-free?



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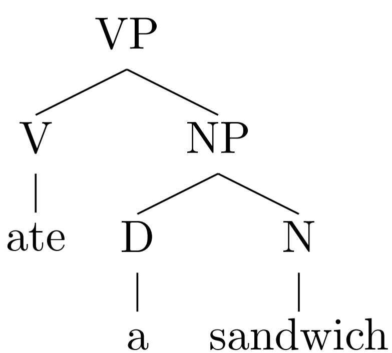

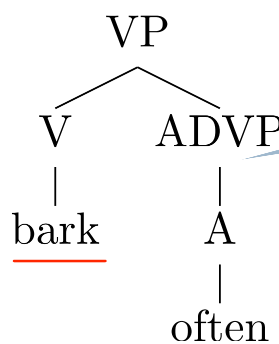

Not grammatical

Matters if we want to generate language (e.g., language modeling) but is this relevant to parsing?

Key problems

- Recognition problem: does the sentence belong to the language defined by CFG?
  - That is: is there a derivation which yields the sentence?
- Parsing problem: what is a (most plausible) derivation (tree) corresponding the sentence?

- Parsing problem encompasses the recognition problem

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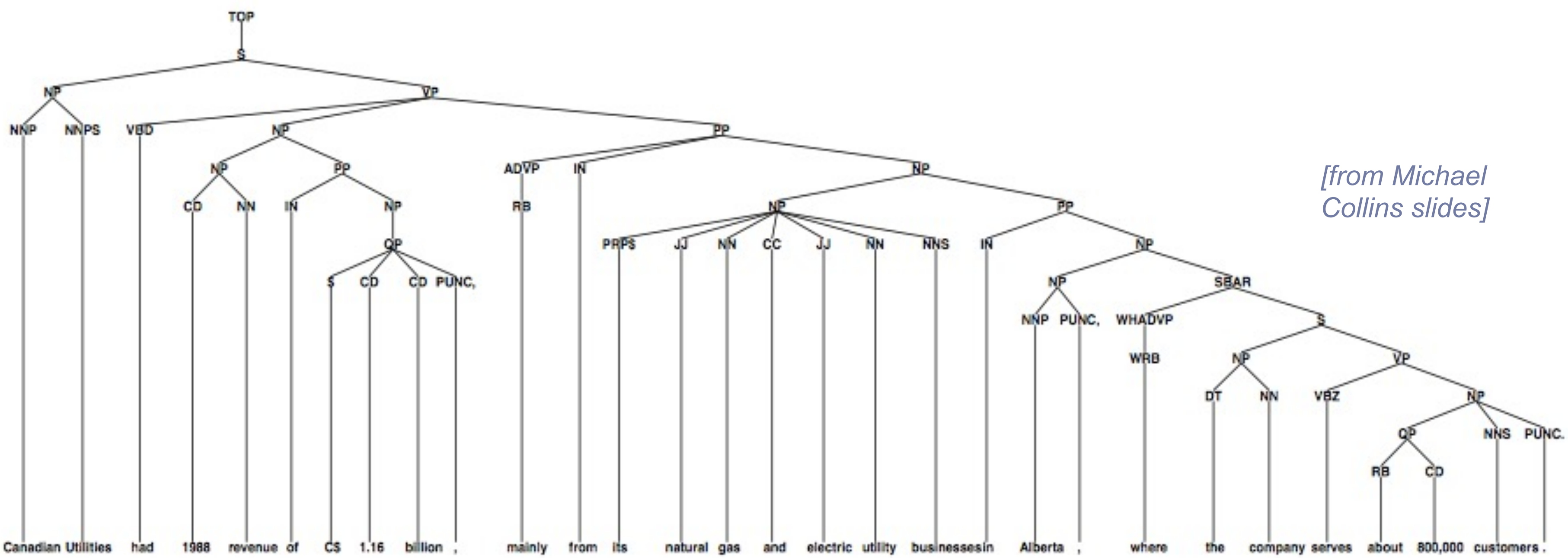
Parsing algorithms

- Goal: compute the structure(s) for an input string given a grammar.
  - (we may want to use the structure to interpret meaning)
  - As usual, ambiguity is a huge problem.

- For correctness: need to find the right structure to get the right meaning.
- For efficiency: searching all possible structures can be very slow
  - want to use parsing for large-scale language tasks

Parsing is hard

- A typical tree from a standard dataset (Penn treebank WSJ)



[from Michael Collins slides]

Canadian Utilities had 1988 revenue of $ 1.16 billion , mainly from its natural gas and electric utility businesses in Alberta , where the company serves about 800,000 customers .

Parser properties

All parsers have two fundamental properties:

- Directionality: the sequence in which the structures are constructed.
  - Top-down: start with root category (S), choose expansions, build down to words.
  - Bottom-up: build subtrees over words, build up to S.
  - Mixed strategies also possible (e.g., left corner parsers)
- Search strategy: the order in which the search space of possible analyses is explored.

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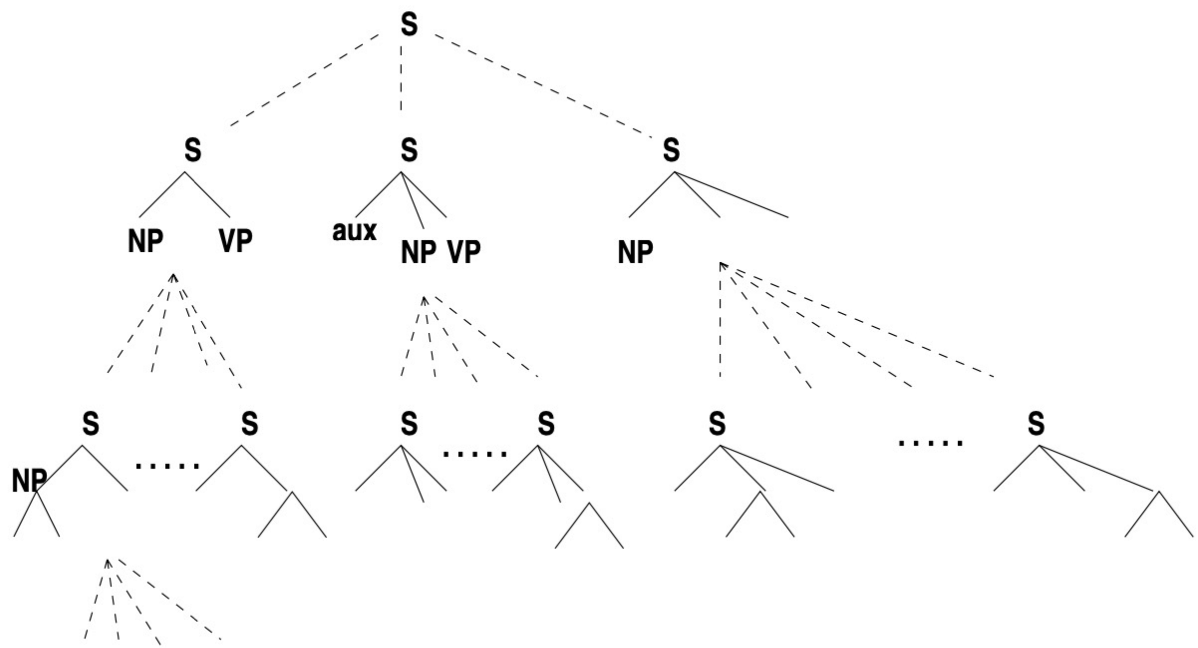
Search space for a top-down parser

- Start with S node.
- Choose one of many possible expansions.
- Each of which has children with many possible expansions...
- etc



Search strategies

All parsers have two fundamental properties:

- Depth-first search: explore one branch of the search space at a time, as far as possible. If this branch is a dead-end, parser needs to backtrack.

- Breadth-first search: expand all possible branches in parallel (or simulated parallel). Requires storing many incomplete parses in memory at once.

- Best-first search: score each partial parse and pursue the highest-scoring options first.

We will now consider a bottom-up parser which uses dynamic programming to explore the space

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CKY algorithm (aka CYK)

- Cocke-Kasami-Younger algorithm
  - Independently discovered in late 60s / early 70s
- An efficient bottom-up parsing algorithm for CFGs
  - can be used both for the recognition and parsing problems
- Very important in NLP (and beyond)
- As we will see, it is generalizable to probabilistic modeling / PCFGs

Constraints on the grammar

- The basic CKY algorithm supports only rules in the *Chomsky Normal Form* (CNF):

$$C \rightarrow x$$

Unary preterminal rules, generation of words given PoS tags
$D \rightarrow the \quad N \rightarrow telescope$

$$C \rightarrow C_1 C_2$$

Binary inner rules (e.g., $S \rightarrow NP\ VP,\ NP \rightarrow D\ \ N$)

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Unary preterminal rules, generation of words given PoS tags
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Binary inner rules (e.g., $S \rightarrow NP\ VP,\ NP \rightarrow D\ \ N$)

- Any CFG can be converted to an equivalent CNF
  - Equivalent means that they define the same language
  - However (syntactic) trees will look differently
  - It is possible to address it but defining such transformations that allows for easy reverse transformation

Transformation to CNF form

- What one need to do to convert to CNF form
  - Get rid of empty (aka epsilon) productions: $C \rightarrow \epsilon$
  - Get rid of unary rules: $C \rightarrow C_1$
  - N-ary rules: $C \rightarrow C_1 \; C_2 \ldots C_n \quad (n > 2)$

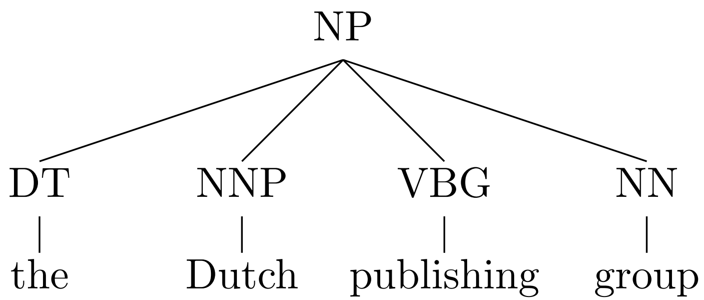
Generally not a problem as there are no empty production in the standard treebanks (or they can be disregarded)

Not a problem, as our CKY algorithm will support unary rules

Crucial to process them, as required for efficient parsing

Transformation to CNF form: binarization

- Consider $NP \rightarrow DT\ \ NNP\ \ VBG\ \ NN$



- How do we get a set of binary rules which are equivalent?

Transformation to CNF form: binarization

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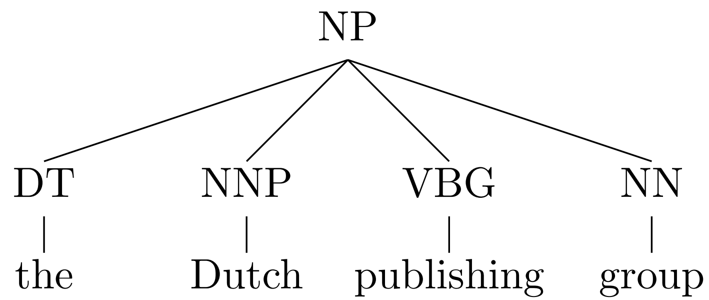


- How do we get a set of binary rules which are equivalent?

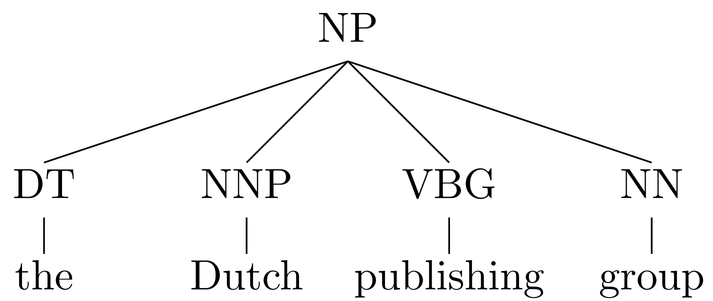
$$NP \rightarrow DT \;\; X$$

$$X \rightarrow NNP \;\; Y$$

$$Y \rightarrow VBG \;\; NN$$

Transformation to CNF form: binarization

- Consider $NP \rightarrow DT \;\; NNP \;\; VBG \;\; NN$



- How do we get a set of binary rules which are equivalent?

$NP \rightarrow DT \;\; X$

$X \rightarrow NNP \;\; Y$

$Y \rightarrow VBG \;\; NN$

- A more systematic way to refer to new non-terminals

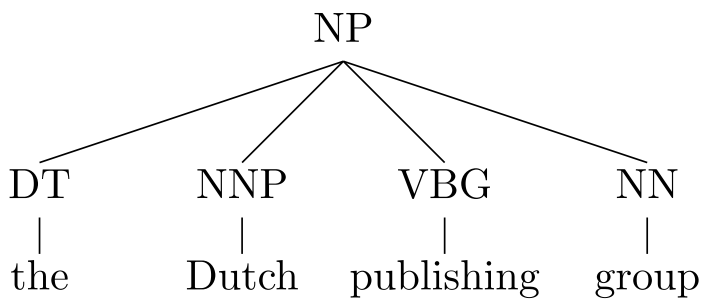
$NP \rightarrow DT \;\; @NP|DT$

$@NP|DT \rightarrow NNP \;\; @NP|DT\_NNP$

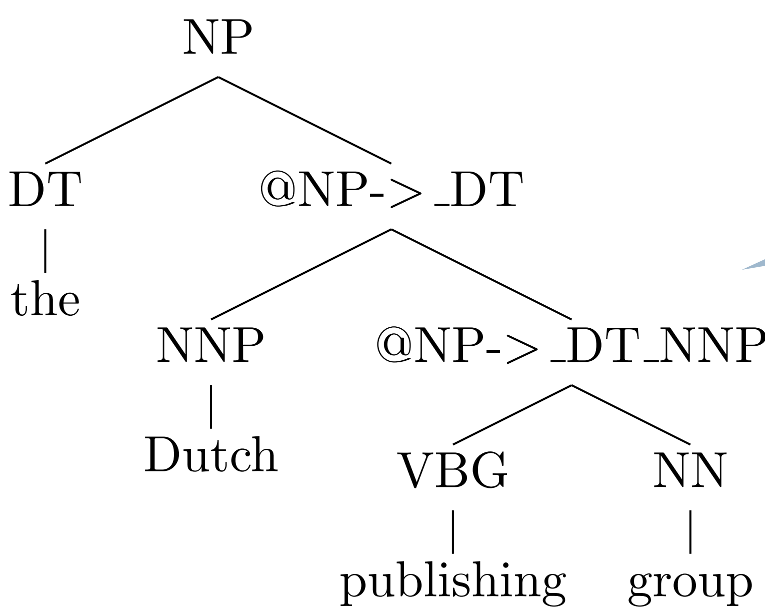
$@NP|DT\_NNP \rightarrow VBG \;\; NN$

Transformation to CNF form: binarization

- Instead of binarizing tules we can binarize trees on preprocessing:



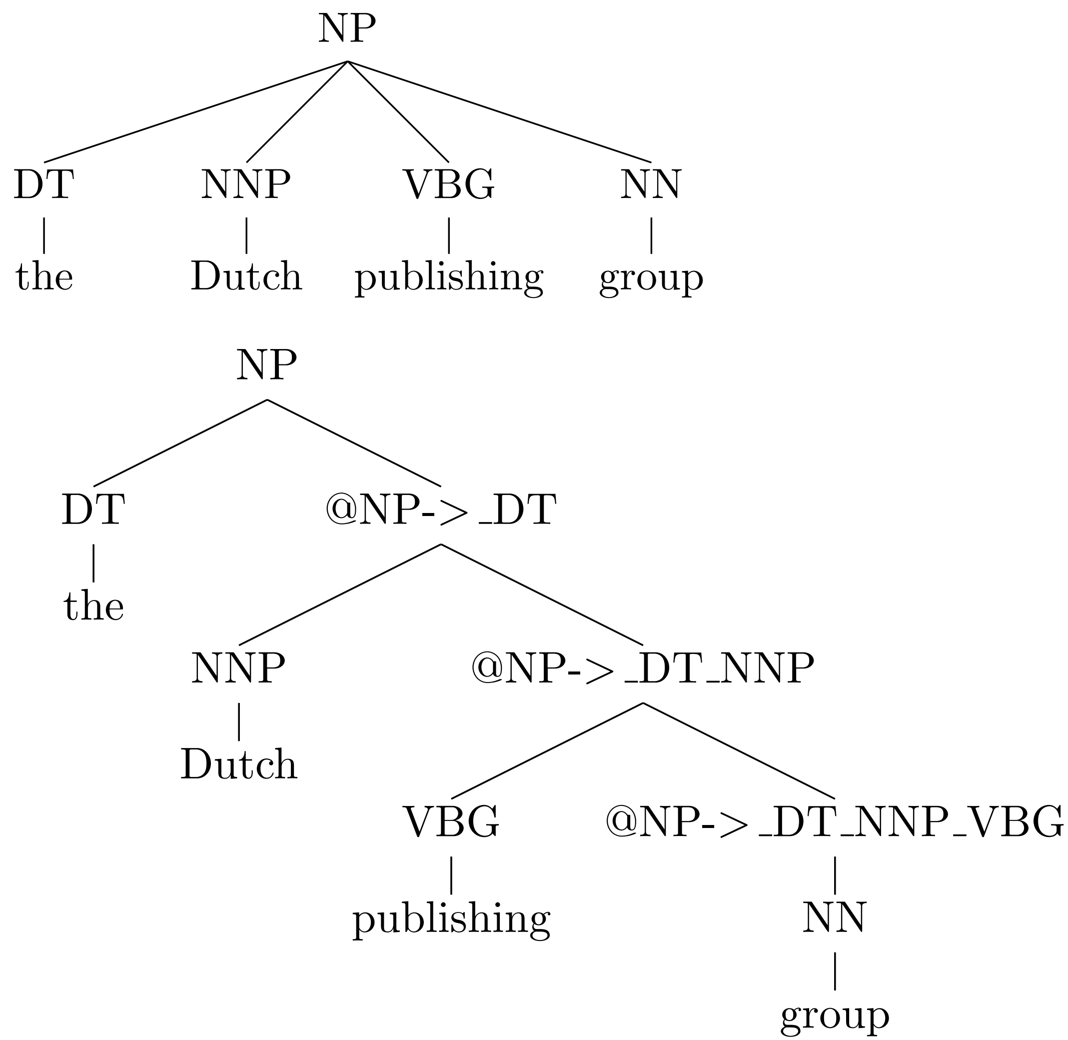
Also known as **lossless Markovization** in the context of PCFGs



Can be easily reversed on postprocessing

Transformation to CNF form: binarization

- Instead of binarizing tules we can binarize trees on preprocessing:



Summary

- Basics of Syntax and Context-Free Grammars
- Classes of Syntactic Parsing Algorithms
- Started with the CKY algorithm – preparing the grammar

Next lectures(s):

- CKY algorithm
- Probabilistic parsing with PCFGs
- PCFG parsing beyond treebank grammars
- Neuralized PCFG algorithms