Foundations for Natural Language Processing
Lecture 14
Syntax and Parsing

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School of informatics

Plan

- Finish with tagging: Unsupervised Estimation with HMMs (EM for HMMs)
- Start with Syntax and Parsing

Recap: Hidden Markov Models

- We will consider the part-of-speech (POS) tagging example

John	**carried**	**a**	**tin**	**can**	**.**
NNP	VBD	DT	NN	NN	.

- A "generative" model, i.e.:
  - Model: Introduce a parameterized model of how both words and tags are generated $P(\mathbf{x}, \mathbf{y}|\theta)$
  - Learning: use a labeled training set to estimate the most likely parameters of the model $\hat{\theta}$
  - Decoding: $\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} P(\mathbf{x}, \mathbf{y}|\theta)$

Recap: Viterbi

a_{ij}	STOP	NN	VB	JJ	RB
START	0	0.5	0.25	0.25	0
NN	0.25	0.25	0.5	0	0
VB	0.25	0.25	0	0.25	0.25
JJ	0	0.75	0	0.25	0
RB	0.5	0.25	0	0.25	0

b_{ik}	time	flies	fast	…	…	…
NN	0.1	0.01	0.01	…	…	…
VB	0.01	0.1	0.01	…	…	…
JJ	0	0	0.1	…	…	…
RB	0	0	0.1	…	…	…

Initialization: $v_i^1 = a_{START,i} b_{i,x^1}, \quad i = 1, \dots, N;$

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

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

	time₁	*flies₂*	*fast₃*	-
NN	0.05	1.25E-4	6.25E-6	-
VB	0.0025	0.0025	6.25E-7	-
JJ	0	0	6.25E-5	-
RB	0	0	6.25E-5 x 0.5	-
STOP	-	-	-	6.25E-5 x 0.5

Recap: 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.

Recap: Forward algorithm (~ a modification of Viterbi)

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

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

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

Recap: EM for Naïve Bayes

		Bayes	your	model	cash	Viagra	class	orderz	spam?
labeled data	lab doc 1	0	1	3	0	0	2	0	-
	lab doc 2	0	2	0	4	0	0	0	+
	lab doc 3	0	2	2	0	0	3	0	-
	lab doc 4	0	3	2	1	3	0	1	+
	lab doc 5	0	1	0	2	0	0	1	+
unlabeled data	unl doc 2	2 x 0.53	2 x0.53	0	0	0	0	0	+ (.53)
		2 x 0.47	2 x 0.47	0	0	0	0	0	- (.47)

$$\hat{P}(\text{your}|+) = (6 + 2 \times 0.53 + \alpha)/(20 + 4 \times 0.53 + \alpha * F)$$

$$\hat{P}(\text{your}|-) = (3 + 2 \times 0.47 + \alpha)/(13 + 3 \times 0.47 + \alpha * F)$$

$$\hat{P}(\text{spam}) = \frac{3 + 0.53}{5 + 1}$$

This is just for one data point

$$\hat{P}(\text{Bayes}|+) = (2 \times 0.53 + \alpha)/(20 + 4 \times 0.53 + \alpha * F)$$

$$\hat{P}(\text{Bayes}|-) = (2 \times 0.47 + \alpha)/(13 + 4 \times 0.47 + \alpha * F)$$

EM for Semi-supervised Learning

1. Train NB on labeled data alone
2. Make soft prediction on on unlabelled data ("E-step")
3. Recompute NB parameters using the soft counts

HMM and Unsupervised Estimation

- N – the number tags, M – vocabulary size
- Parameters (to be estimated from the training set):
  - Transition probabilities $a_{ji} = P(y^t = i | y^{t-1} = j)$, A - [N x N] matrix
  - Emission probabilities $b_{ik} = P(x^t = k | y^t = i)$, B - [N x M] matrix
- Training corpus:
  - $\boldsymbol{x}^{(1)}=$ (In, an, Oct., 19, review, of, ….)
  - $\boldsymbol{x}^{(2)}=$ (Ms., Haag, plays, Elianti,.)
  - …
  - $\boldsymbol{x}^{(L)}=$ (The, company, said,…)

Estimation is trickier: no examples labelled with the right 'answers': all we see are outputs, state sequence is hidden.

Circularity

- If we know the state sequence, we can find the best parameters
  - E.g., use MLE / normalized counts
- If we know parameters, we can find the best state sequence
  - Use Viterbi
- But we do not know them either

- Does not fit the self-training algorithm, but can we make EM work in this setting?

Expectation-maximization (EM)

- As in spelling correction, we can use EM to bootstrap, iteratively updating the parameters and hidden variables.
  - Initialize parameters, $A^{(0)}$ and $B^{(0)}$
  - At each iteration k:
    - E-step: Compute expected counts using $A^{(k-1)}$ and $B^{(k-1)}$
    - M-step: set $A^{(k-1)}$ and $B^{(k-1)}$ using MLE on the expected counts
- Repeat until doesn't converge (a stopping criteria).

Expected counts??

- Counting transitions from ($y^{t-1}= i, y^t=j$):
- Real counts:
  - count 1 each time we see *($y^{t-1}= i, y^t=j$)* in true tag sequence.
- Expected counts:
  - With current A and B, compute probs of all possible tag sequences.
  - If sequence **y** has probability p, count p for each *($y^{t-1}= i, y^t=j$)* in **y**.
  - Add up these fractional counts across all possible sequences

Example

- Notionally, we compute expected counts as follows:

Possible tag sequence			Probability of the sequence
N	N	N	p_1
N	V	N	p_2
N	N	V	p_3
aa	bb	cc	- Sequence of observations (words)

$C_T(N, N) =$

Example

- Notionally, we compute expected counts as follows:

Possible tag sequence	Probability of the sequence
N N N	p_1
N V N	p_2
N N V	p_3
aa bb cc	- Sequence of observations (words)

$$C_T(N, N) = 2\,p_1 + p_3$$

Forward-Backward algorithm

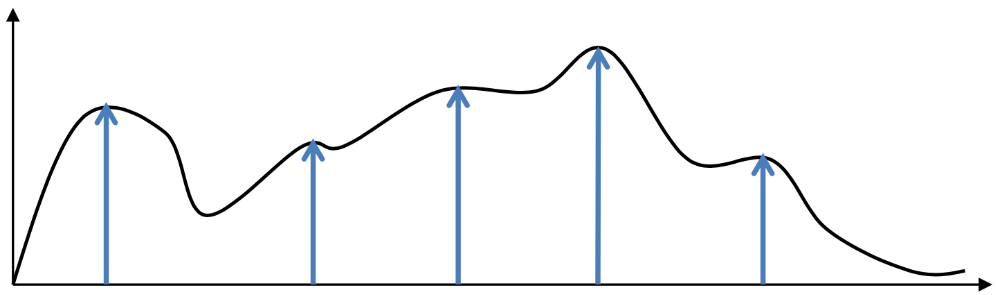
- As usual, avoid enumerating all possible sequences.
- Forward-Backward (Baum-Welch) algorithm computes expected counts (using forward probabilities and backward probabilities)

$$P(y^{t-1} = i, y^t = j | x)$$

- EM idea is much more general: can use for many latent variable models.

EM

- EM is guaranteed to find a local maximum of the likelihood.



- Not guaranteed to find global maximum.
- Practical issues: initialization, random restarts, early stopping. Fact is, it doesn't work well for learning POS taggers!

Summary for HMM / Tagging

- HMM : a generative model of sentences using hidden state sequences
- Dynamic programming algorithms to compute
  - Best tag sequence given words (Viterbi algorithm)
  - Likelihood (forward algorithm)
  - Best parameters from unannotated corpus (forward-backward, an instance of EM)

You can read details of forward-backward in the text-book, not required for the exam (but Viterbi and Forward are)

Syntax

- Basics of Syntax, Context-Free Grammars
- Classes of Syntactic Parsing Algorithms
- Start with the CKY algorithm

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.
- Useful for various tasks, but a really accurate model of language needs more than a fixed-length history!

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:

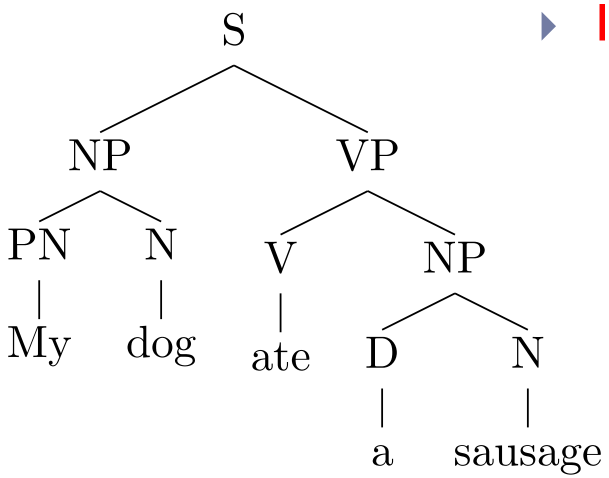
    Colorless green ideas sleep furiously
- However we'll see shortly that the reason we care about syntax is mainly for interpreting meaning.

Theories of syntax

- We'll look at two theories of syntax:
  - Constituency (aka phrase) structures: next two classes
  - Dependency structures: during the last lecture on parsing

- These can be viewed as different models of language behaviour. As with other models, we will look at
  - What each model can capture, and what it cannot.
  - Algorithms that provide syntactic analyses for sentences using these models (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 $X \to Y_1, Y_2, \ldots, Y_n$, where $n \geq 0$, $X \in V,\ Y_i \in V \cup \Sigma$

    $$S \to NP\ \ VP \qquad N \to girl$$
    $$NP \to D\ \ N \qquad N \to telescope$$
    $$NP \to PN \qquad V \to saw$$
    $$NP \to NP\ \ PP \qquad V \to eat$$
    $$PP \to P\ \ NP \qquad \ldots$$
    $$\ldots$$

  - 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

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

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

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

$$PP \rightarrow P \;\; NP$$

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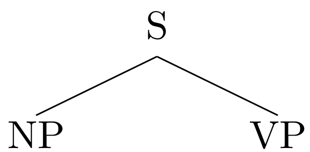

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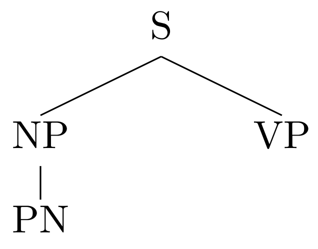

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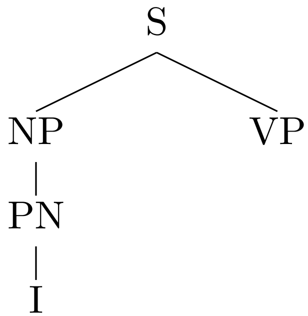

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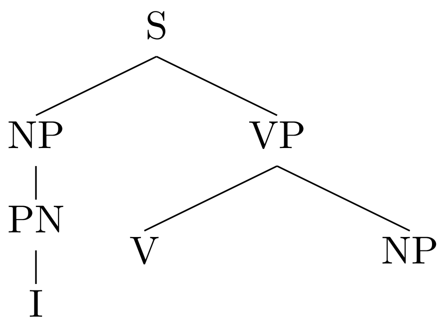

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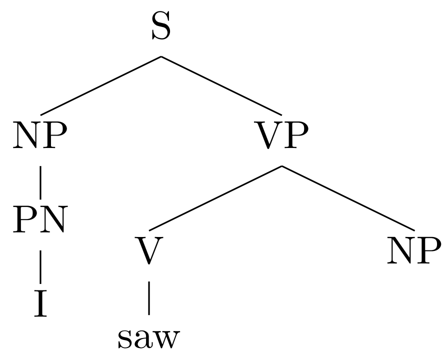

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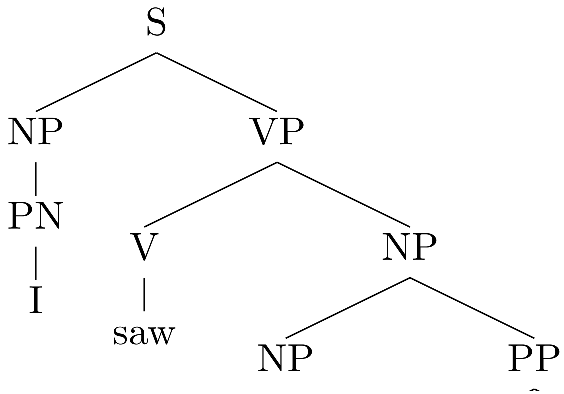

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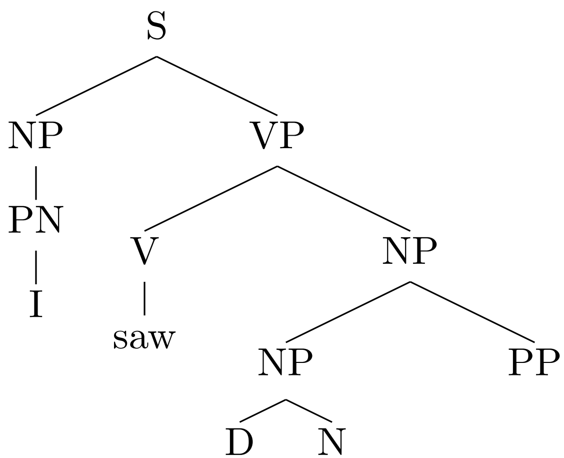

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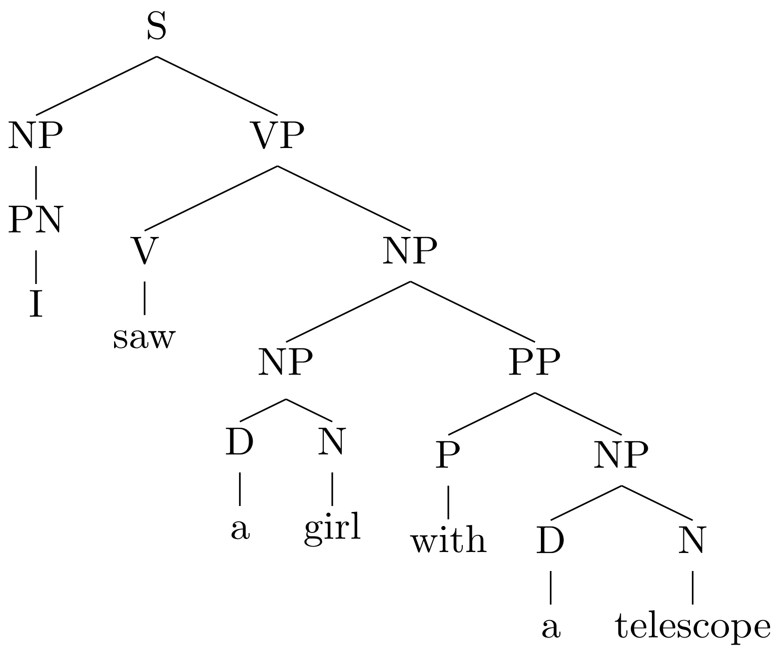
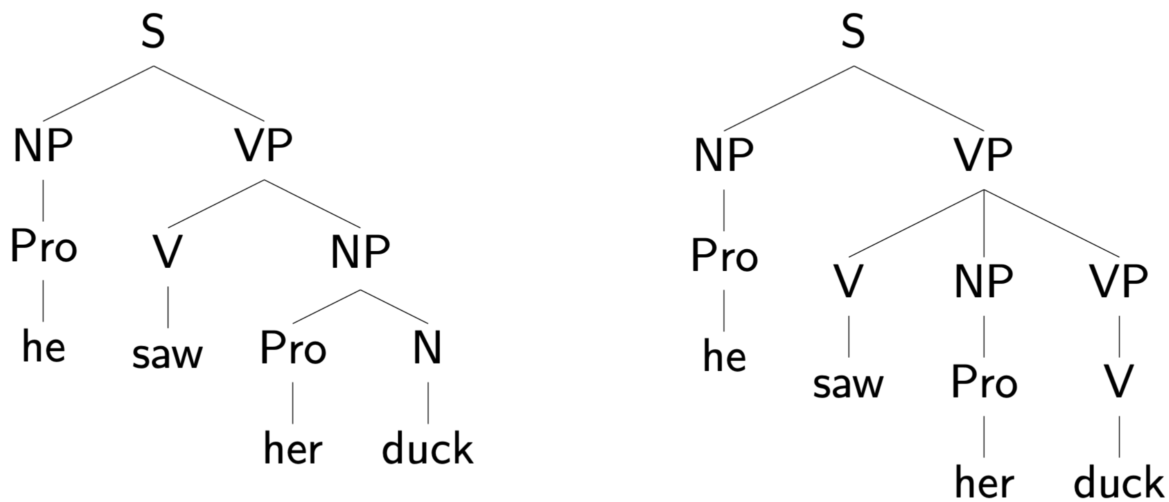


CFG defines both:

- 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

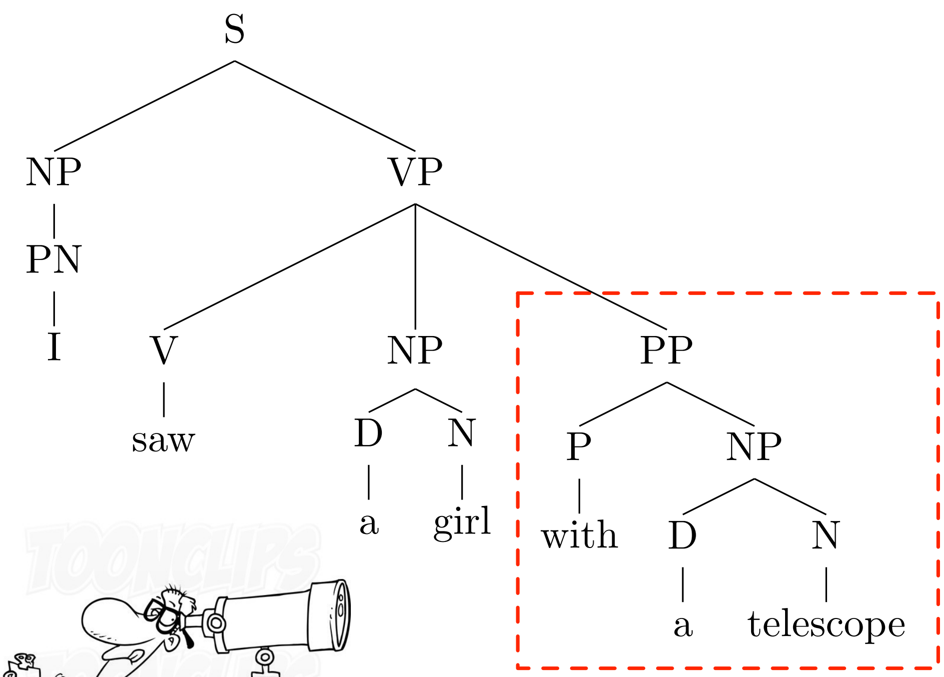
- Some sentences have structural ambiguity even **without** part-of-speech ambiguity. This is called attachment ambiguity.
  - Depends on where different phrases attach in the tree.
  - Different attachments have different meanings:

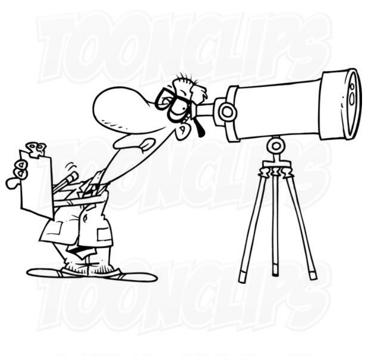
  I saw a girl with a telescope
  She ate the pizza on the floor
  Good boys and girls get presents from Santa

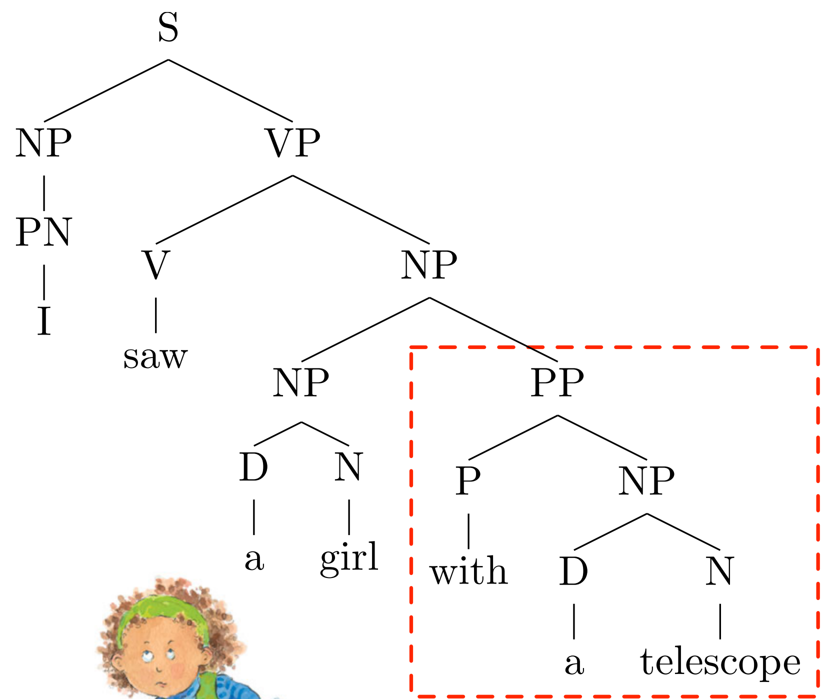
- Next slide shows trees for the first example: prepositional phrase (PP) attachment ambiguity.

Prepositional Phrase (PP-) Attachment Ambiguity

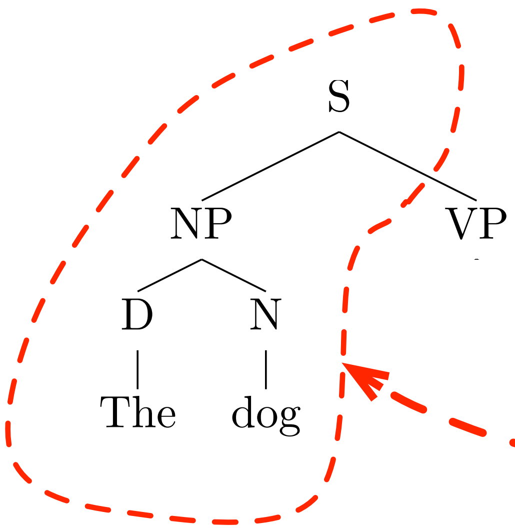
- Prepositional phrase attachment ambiguity





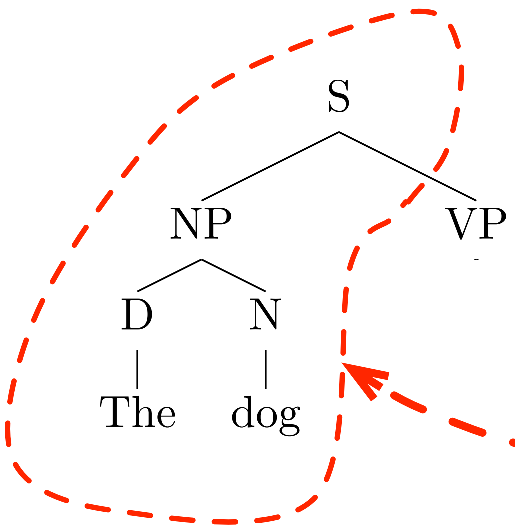


Why context-free?



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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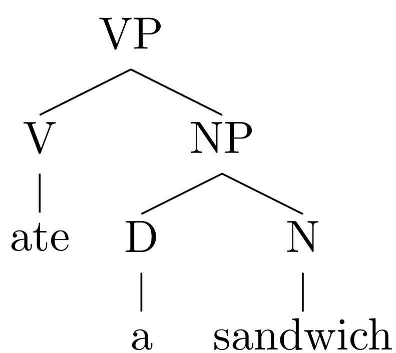
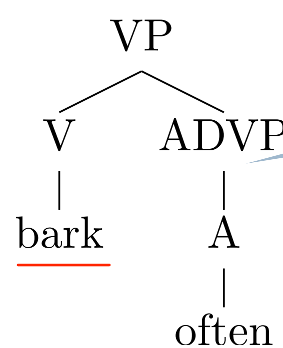
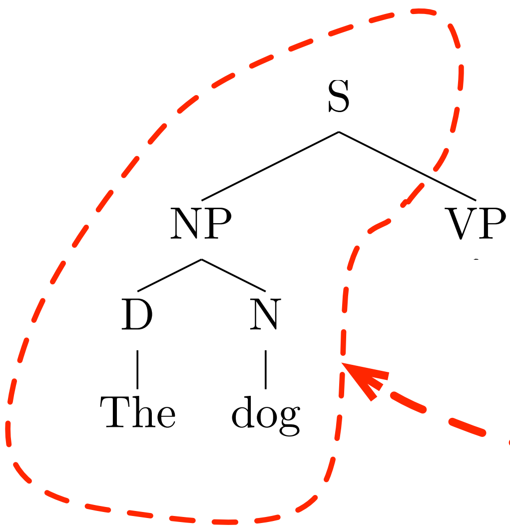




Not grammatical

Why context-free?



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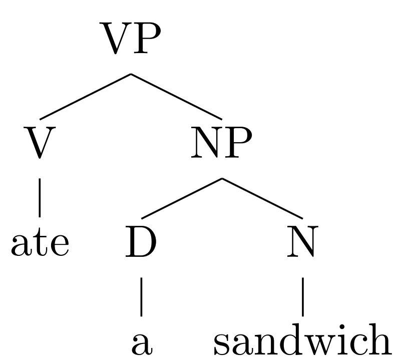
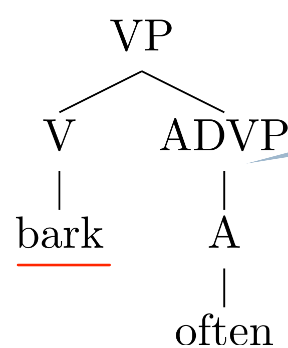




Not grammatical

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

Today

- Basics of Syntax and Context-Free Grammars
- Classes of Syntactic Parsing Algorithms
- Start with the CKY algorithm

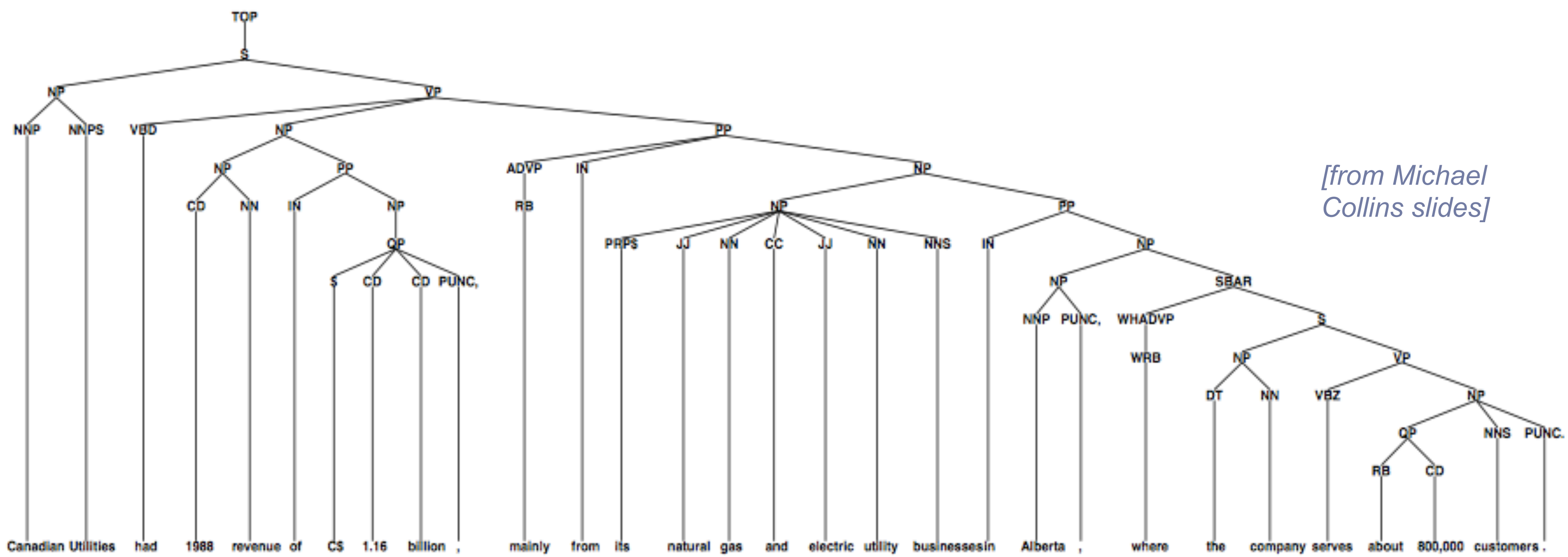
Parsing algorithms

- 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)
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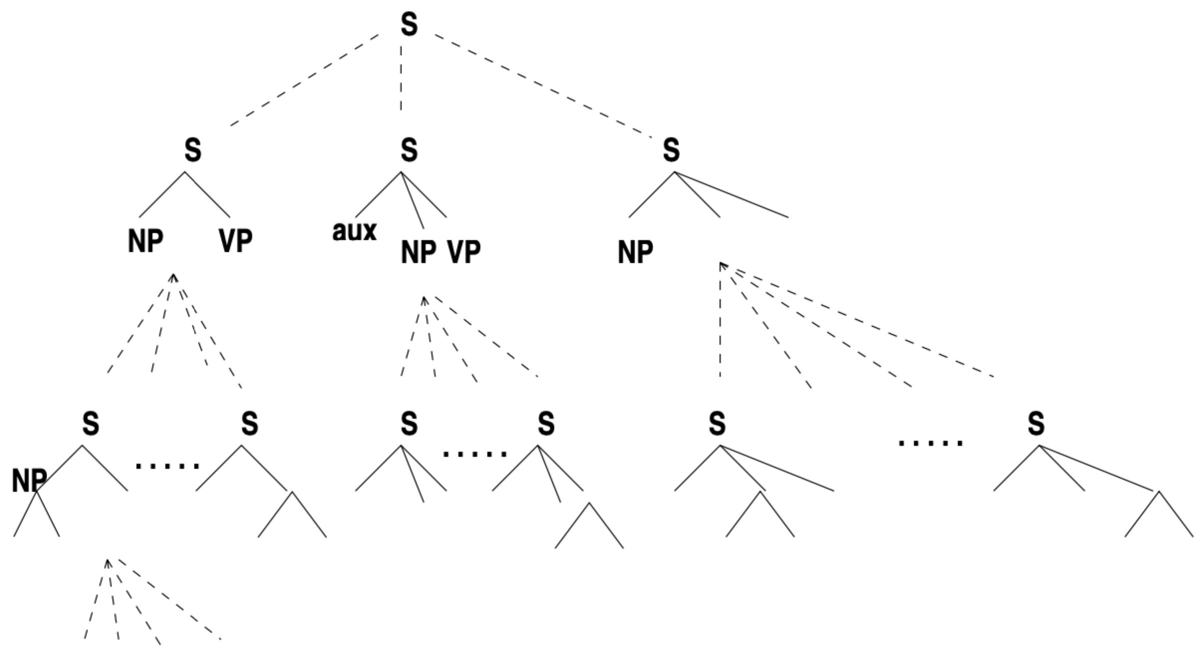
Search space for a top-down parser

- 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

Summary

- Basics of Syntax and Context-Free Grammars
- Classes of Syntactic Parsing Algorithms

Next time:

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