Introduction to NLP

Probabilistic Parsing

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Overview

Parsing with Probabilistic Context-free Grammars (PCFGs)

Probabilistic Cocke-Younger-Kasami (CYK) algorithm

Problems with and solutions for PCFGs

Comparison of LMs, HMMs and PCFGs

Summary

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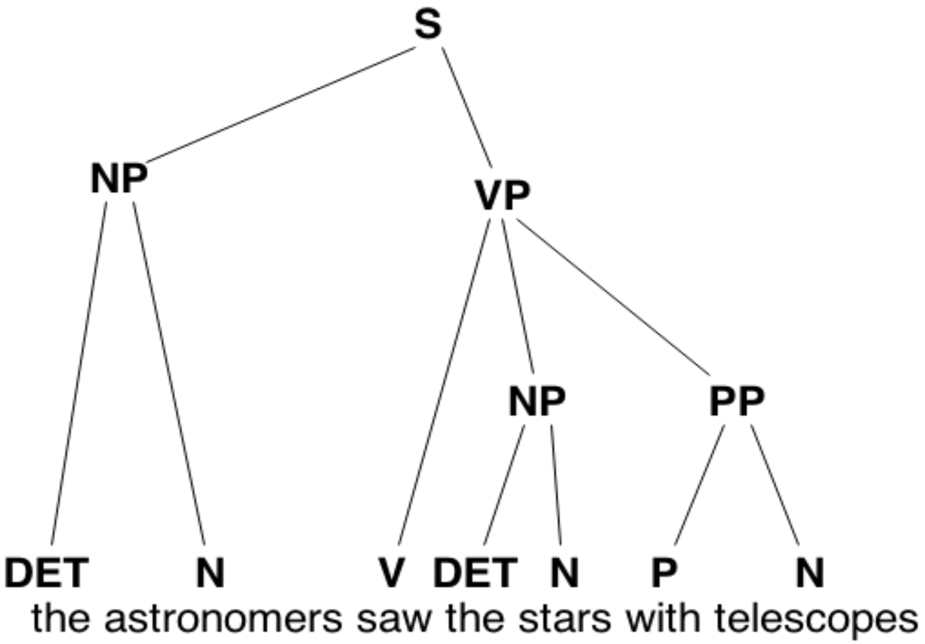
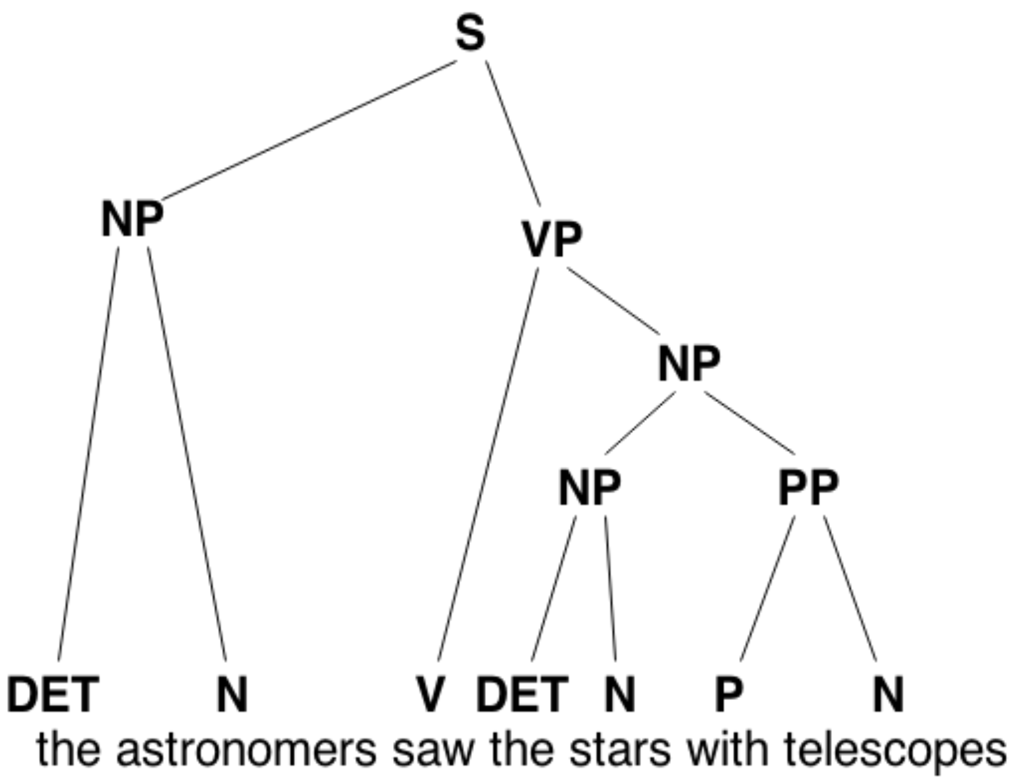
Parsing

Parsing is the problem of finding the tree structure of a sentence



Ambiguity

Parses are often ambiguous



Probabilistic Grammars: Motivation

Probabilities on parses allow us to choose the best (most-likely) parse tree

Probabilities also allow parsers to be language models

- Better handling of language structure
- Generalization over part-of-speech
- Constrain next word candidates
- More complexity

No framework has become truly standard

Context-free grammars

Recall, a context-free grammar G=(N,Σ,P,S) consists of:

A set of non-terminal symbols N

e.g., 'N', 'VP', 'S'

A set of terminal symbols Σ

e.g., 'cat', 'astronomer', 'the'

A set of productions P

e.g., 'S $\longrightarrow$ NP VP'

A start symbol

Normally 'S'

Probabilistic context-free grammar

A probabilistic context-free grammar $G=(N,\Sigma,P,S,D)$ consists of:

- N, Σ, P, S as for a CFG
- A function $D:P\rightarrow[0,1]$ which assigns a probability to each production

A PCFG is consistent iff

$$\sum_{\{\beta\,:\,A\rightarrow\beta\in P\}} D(A\rightarrow\beta) = 1 \quad \forall A\in N$$

And there are no infinite derivations for any finite string (e.g., $S\rightarrow S$)

Notation
Lowercase letters: Terminal (word), e.g. a,the
Capital letters: Non-terminal, e.g., N, V
Greek letters: Sequence of terminal and non-terminals
ϵ : Empty sequence

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Example: PCFG

Rule	Prob	Rule	Prob
S $\longrightarrow$ NP VP	0.80	VP $\longrightarrow$ V NP	0.90
S $\longrightarrow$ Aux NP VP	0.20	VP $\longrightarrow$ V NP NP	0.10
NP $\longrightarrow$ PN	0.45	N $\longrightarrow$ flights	1.00
NP $\longrightarrow$ Nom	0.05	V $\longrightarrow$ book	1.00
NP $\longrightarrow$ Pro	0.50	Aux $\longrightarrow$ can	1.00
Nom $\longrightarrow$ N	0.95	PN $\longrightarrow$ Lufthansa	1.00
Nom $\longrightarrow$ PN Nom	0.05	Pro $\longrightarrow$ you	1.00

Calculating the probability of a parse

We wish to know how likely a parse T is, given input S

$$P(T|S) = P(T,S)/P(S)$$

Ergo, the best parse is $$T^* = \arg\max_T P(T,S)$$

And as the parse tree contains all words in the sentence

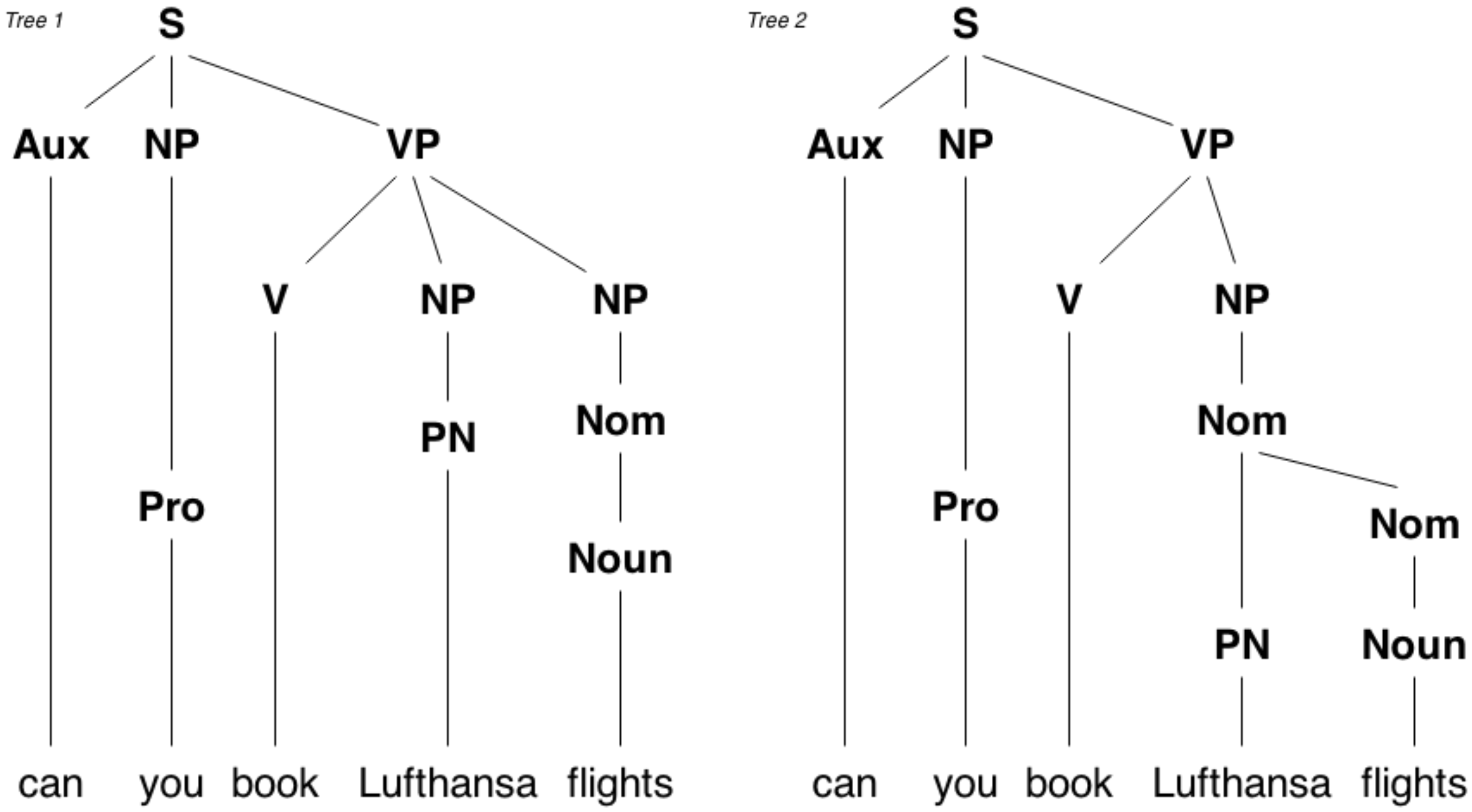
$$P(T,S) = P(T)P(S|T) = P(T)$$

Hence

$$P(T,S) = \prod_{n \in T} D(r(n))$$

Where r(n) is the rule used to generate n

Example: Parsing with PCFG



Example: Parsing with PCFG

Tree 1

$S \longrightarrow Aux\ NP\ VP$	0.20	$Aux \longrightarrow can$	1.00
$NP \longrightarrow Pro$	0.50	$Pro \longrightarrow you$	1.00
$VP \longrightarrow V\ NP\ NP$	0.10	$V \longrightarrow book$	1.00
$NP \longrightarrow Nom$	0.05	$PN \longrightarrow Lufthansa$	1.00
$NP \longrightarrow PN$	0.45	$N \longrightarrow flights$	1.00
$Nom \longrightarrow N$	0.95		

P(Tree 1) = 0.2 × 0.5 × 0.1 × 0.05 × 0.45 × 0.95 × 1.0 × 1.0 × 1.0 × 1.0 × 1.0

= 0.00021

Exercise: Tree 2

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Finding the best parse

It is not practical to find all parse trees (exponential number)

Recall, we can find the parse of a CFG in $\mathcal{O}(N^3)$

We can also find the best parse in $\mathcal{O}(N^3)$

Two most commonly used algorithms are easily adaptable to PCFG

- Earley algorithm
- Cocke-Younger-Kasami (CYK) algorithm

Probabilistic Cocke-Younger-Kasami Algorithm

CYK is essentially a bottom-up parser

Can be adapted to PCFGs with dynamic programming

Input:

- A PCFG
- n words $w_1,\ldots,w_n$

Data structure:

- A table $t_{i,j,a} \in \mathbb{R}$ where $1 \leq i < j \leq n$ and $a \in N$

Output:

- The best parse $T = \arg\max_T P(T)$

CYK

can	you	book	Lufthansa	flights	*j - i*
Aux: 1.0	Pro: 1.0	V: 1.0	PN: 1.0	N: 1.0	1
					2
					3
					4
					5

Rule:
Aux → can : 1.0
Pro → you : 1.0
V → book : 1.0
PN → Lufthansa : 1.0
N → flights : 1.0

CYK

can	you	book	Lufthansa	flights	*j - i*
Aux: 1.0	Pro: 1.0 NP: 0.5	V: 1.0	PN: 1.0 NP: 0.45	N: 1.0 Nom: 0.95 NP: 0.0475	1
					2
					3
					4
					5

Rule:
NP → Pro : 0.5
NP → PN : 0.45
Nom → N : 0.95
NP → Nom : 0.05

CYK

can	you	book	Lufthansa	flights	*j - i*
Aux: 1.0	Pro: 1.0 NP: 0.5	V: 1.0	PN: 1.0 NP: 0.45	N: 1.0 Nom: 0.95 NP: 0.0475	1
			VP: 0.41	Nom: 0.10 NP: 0.005	2
					3
					4
					5

Rule:
VP → V NP : 0.90
Nom → PN Nom : 0.10
NP → Nom : 0.05

CYK

can	you	book	Lufthansa	flights	*j - i*
Aux: 1.0	Pro: 1.0 NP: 0.5	V: 1.0	PN: 1.0 NP: 0.45	N: 1.0 Nom: 0.95 NP: 0.0475	1
			VP: 0.41	Nom: 0.10 NP: 0.005	2
				VP: 0.004 ~~VP: 0.002~~	3
					4
					5

Rule:
VP → V NP NP : 0.10
VP → V NP : 0.90

Choose VP → V NP as
0.9 × 1.0 × 0.005 >
0.1 × 1.0 × 0.45 ×0.0475

CYK

can	you	book	Lufthansa	flights	*j - i*
Aux: 1.0	Pro: 1.0 NP: 0.5	V: 1.0	PN: 1.0 NP: 0.45	N: 1.0 Nom: 0.95 NP: 0.0475	1
			VP: 0.41	Nom: 0.10 NP: 0.005	2
			S: 0.16	VP: 0.004	3
			S: 0.04	S: 0.0017	4
				S: 0.00043	5

Rule:
S → Aux NP VP : 0.20
S → NP VP : 0.80

CYK Algorithm

Set $t_{i,j,a}$ = -∞ for all values

For $i = 1, \ldots, n$

  For $A \rightarrow w_i \in P$

    $t_{i,i+1,A} = D(A \rightarrow w_i)$

For $k = 1, \ldots, n$; $i = 1, \ldots, n - k + 1$; $j = i + k$

  For $A \rightarrow \beta \in P$

    If β matches between i and j

      $S = D(A \rightarrow \beta) \times \prod_{i',j',A'} t_{i',j',A'}$ where $\{i',j',A\}$ are the matches

      If $s > t_{i,j,A}$

        $t_{i,j,A} = s$

Chomsky Normal Form

First, we define Chomsky Normal Form as a grammar such that every rule is of the form:

$A \longrightarrow BC$
$A \longrightarrow a$
$A \longrightarrow \epsilon$

It is known that for any CFG G there is a weakly equivalent grammar CNF(G) in Chomsky Normal Form.

Chomsky Normal Form

CYK is more efficient and easier to implement with a CNF grammar

To convert to normal formal:

Merge rules with a single non-terminal RHS

e.g., Nom→N:0.95, N→flights:1.0 to Nom→flights:0.95

Split rules with more than two non-terminal RHSs

e.g., S→Aux NP VP:0.20 to S→Aux X:0.20, X→NP VP:1.0

CYK for language modelling

The CYK algorithm can be adapted to generate language models scores

How? (Think about Forward Algorithm last week)

Supervised learning of PCFGs

If we have a gold-standard corpus of known trees we can learn from this

- Corpus of trees is called a **treebank**

PCFG probabilities can be obtained by counting

$$D(A \rightarrow \beta) = \frac{c(A \rightarrow \beta)}{c(A)}$$

Smoothing can be applied.

Unsupervised learning of PCFGs

- Suppose we have the grammar but not the probabilities
- We cannot just apply our grammar as there are many ambiguous parse
- We can apply a method called the **Inside-Outside algorithm,** analogous to the forward-backward algorithm
  - Learn probabilities by **expectation maximization.**
- Can be useful in a semi-supervised setting
  - Learning from a treebank and a larger unannotated corpus

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Lexical Dependencies

In a CFG the expansion of one non-terminal is independent of any other non-terminal

In Francis et. al (1999)

Subjects are

- 91% pronouns
- 9% lexical noun phrases

Direct objects are

- 34% pronouns
- 66% lexical noun phrases

Ergo, we would need to distinguish between *NP* in subject and direct object positions

Francis, H. S., Gregory, M. L., and Michaelis, L. A. (1999). Are lexical subjects deviant?. In CLS-99.

Lexical Attachment

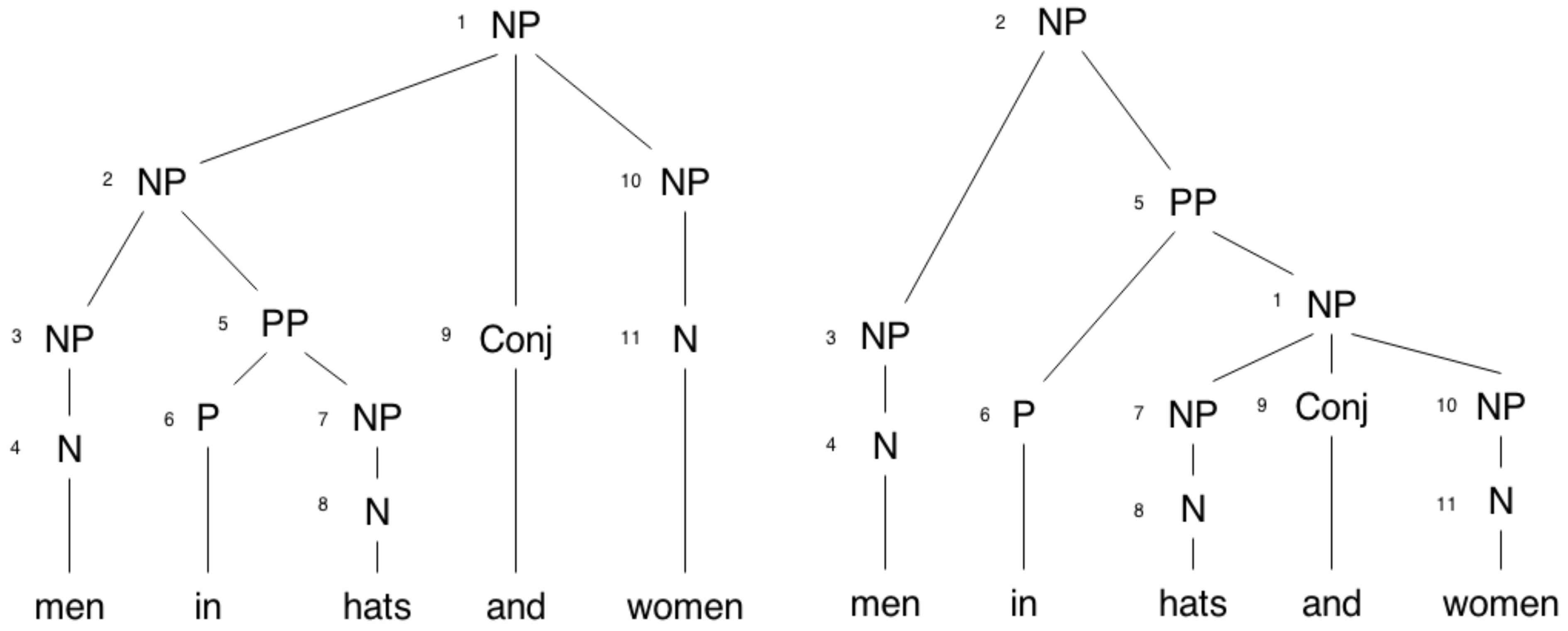
Lexical attachment is very word dependent

For example:

he hit the man with a bat
he hit the man with a hat

PCFGs cannot model lexical dependencies

Parse ambiguity



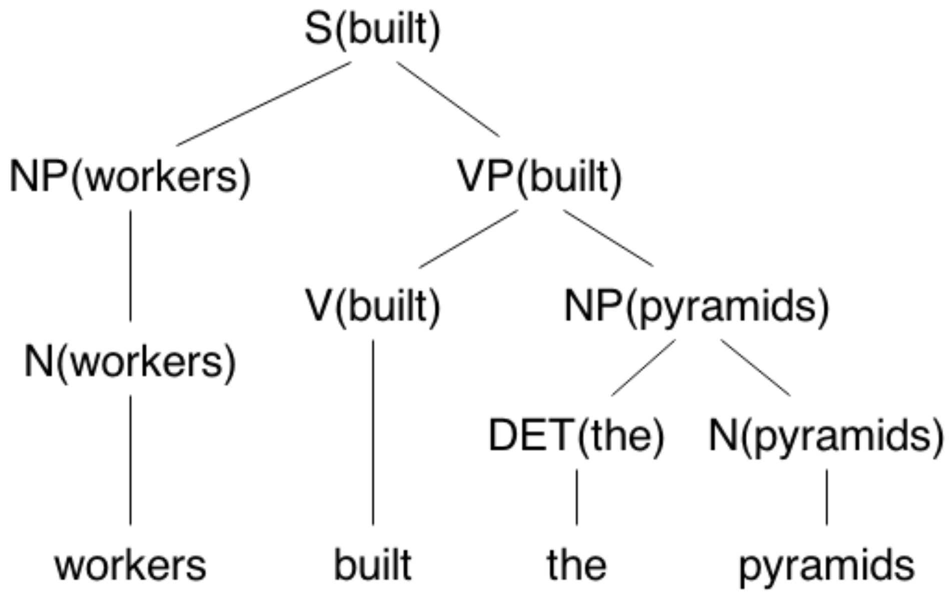
Formalisms for statistical parsing

We will look at two solutions for parsing:

- Lexicalized PCFGs
  - Further differentiate non-terminals by associating them with lexical items
  - Leads to increased sparsity
- Dependency grammars
  - Model links between individual words in the parse
  - Complex to combine with standard CFG

Lexicalized PCFGs

In a lexicalized grammar each non-terminal is further distinguished with a terminal



Heuristic rules decide which non-terminal is the head of the parent

Lexicalized PCFGs

Lexicalizing the grammar creates many more rules

- Extremely sparse

It is common to make some partial independence assumption, e.g.,

$$P(VP(\text{built}) \rightarrow V(\text{built})\ NP(\text{pyramids})) \simeq$$
$$P(VP(\text{built}) \rightarrow V(\cdot)\ NP(\cdot))P(VP(\text{built})|NP(\text{pyramids}))$$

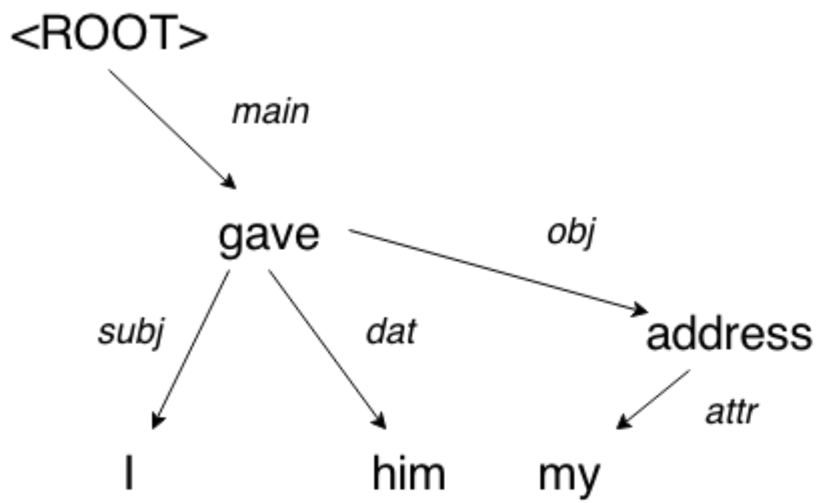
In addition, most parses still apply significant smoothing methods (see lecture 3)

Dependency grammars

Dependency grammars are different to constituency grammars as

- Links are directed and between words
- Links have labels (e.g., ‘subj’)
- They form an acyclic graph

Dependency grammars are especially good for languages with *free word order*



Evaluation of Parsing

Parsers are generally evaluated according to the PARSEVAL metrics

$$\text{recall} = \frac{\#\ \text{correct constituents in parse}}{\#\ \text{consituents in treebank}}$$

$$\text{precision} = \frac{\#\ \text{correct constituents in parse}}{\#\ \text{consituents in parse}}$$

In addition we report cross-brackets

This is where the parser outputs ((A B) C) but the candidate is (A (B C))

Modern parsers achieve 90%+ precision and recall and 1% cross-bracketing

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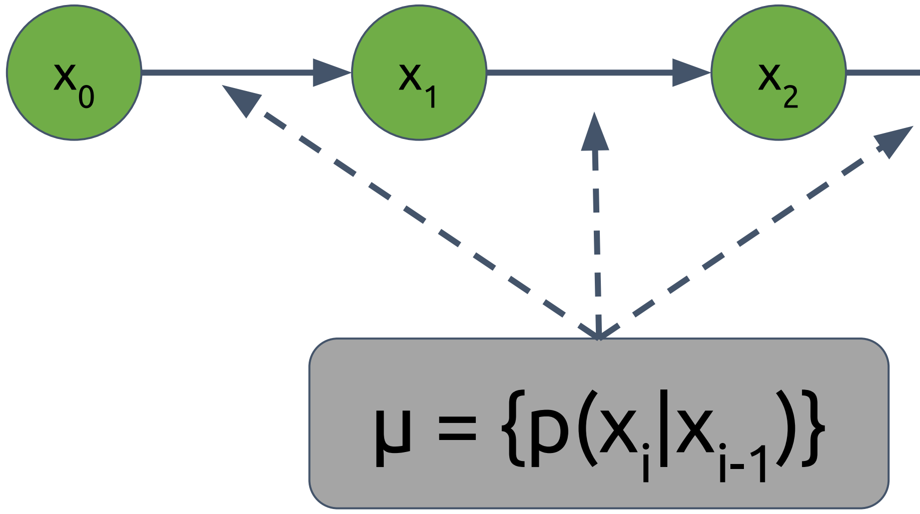
LMs, HMMs and PCFGs

Language models, **Hidden Markov Models** and **Probabilistic Context Free Grammars** are special cases of **probabilistic graphical models**

They consist of

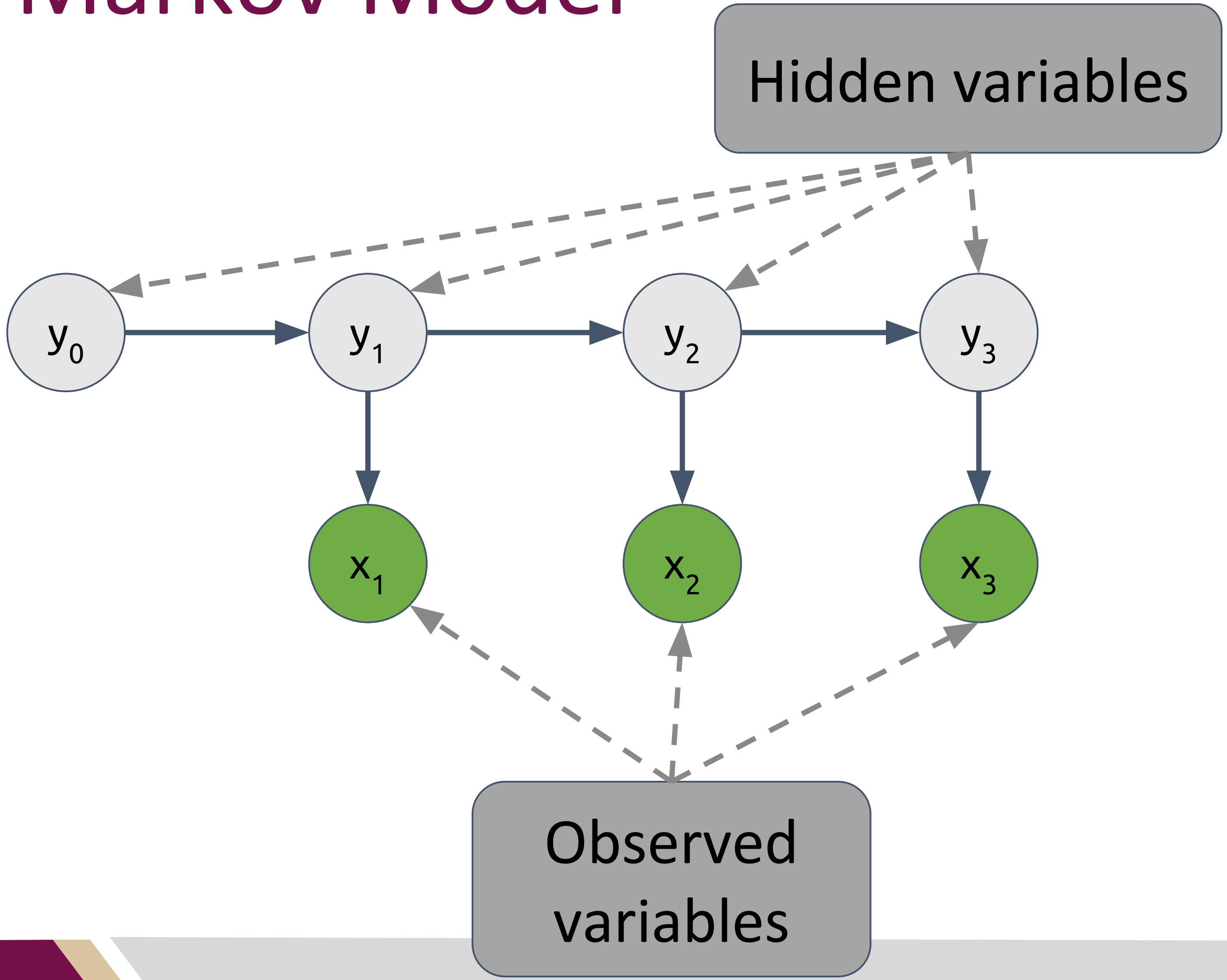
- A set of observed variables X
- A set of hidden variables Y
- A set of parameters (probabilities) μ
- An independence assumption - this generates the structure of the model

Bigram Language Model

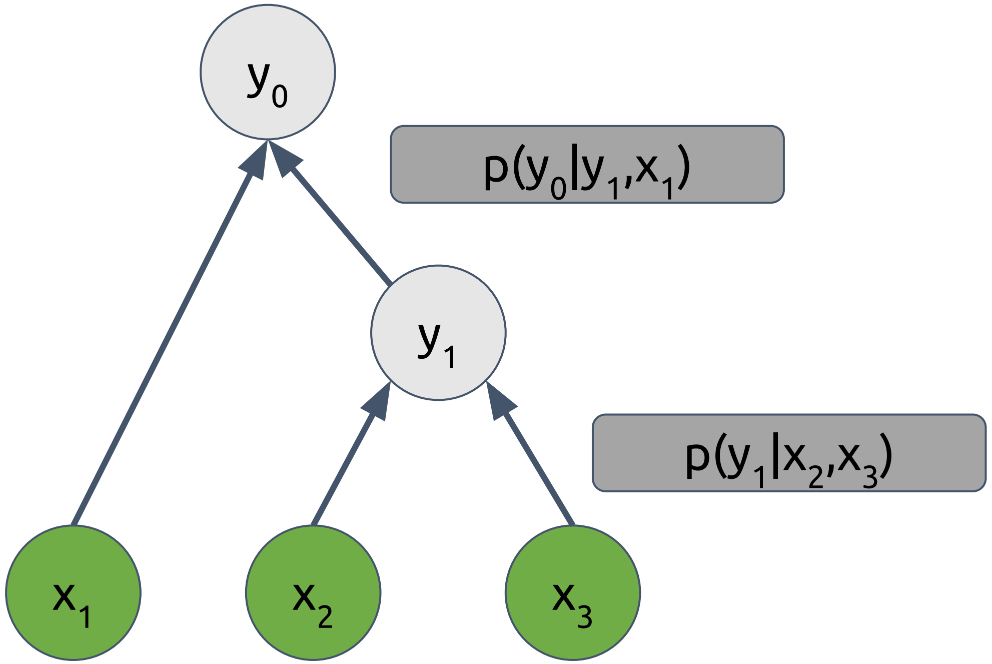


No hidden variables!

Hidden Markov Model



Probabilistic Context-Free Grammar



Problems for Probabilistic Graphical Models

Probability of observed sequence

$p(X|\mu) = \Sigma_Y\, p(X,Y|\mu)$

Most likely hidden state

$\max_Y\, p(X,Y|\mu)$

Dynamic Programming

Learning problem

Supervised: $\max_\mu\, p(X,Y|\mu)$

Unsupervised: $\max_{\mu,Y}\, p(X,Y|\mu)$

Counting

E-M algorithm

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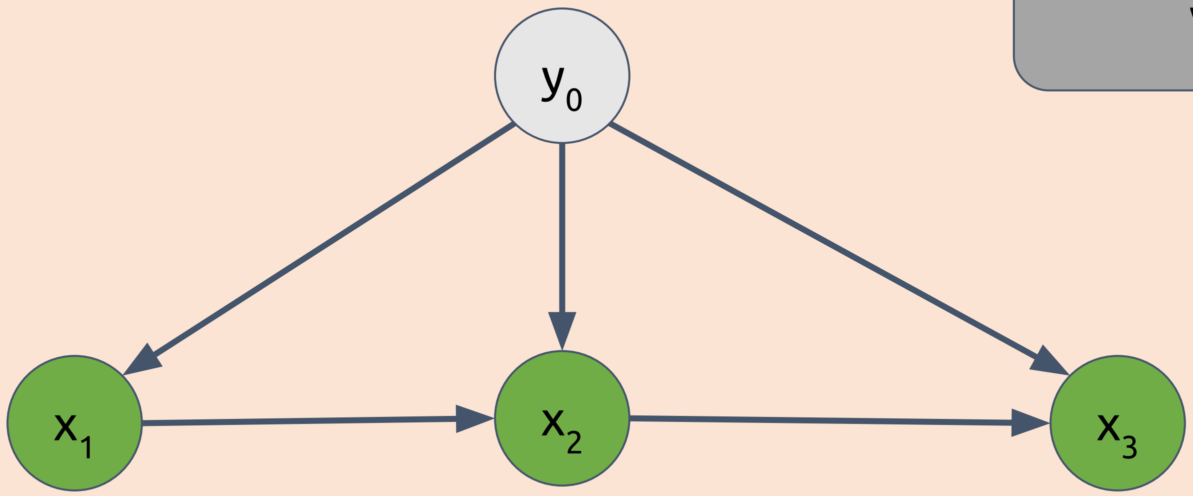
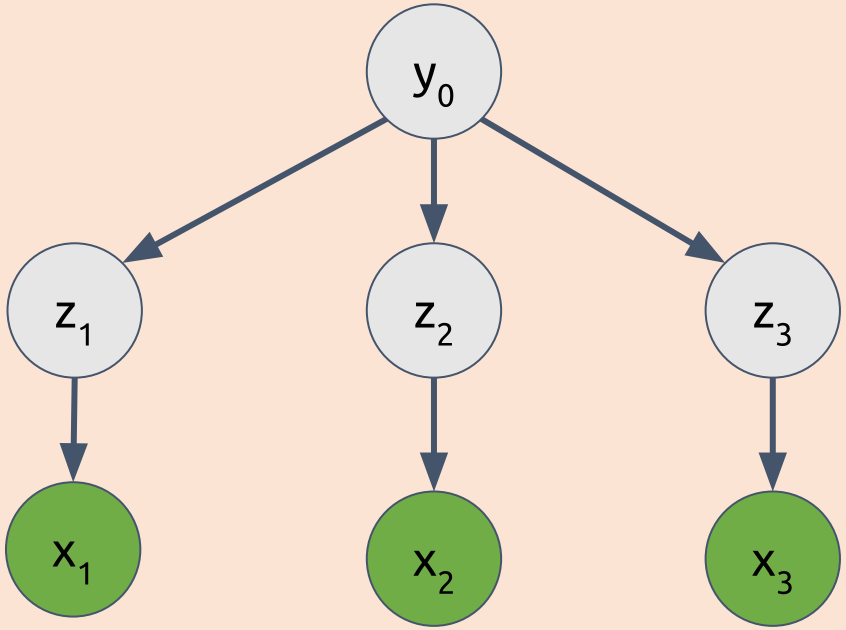
Topic Models



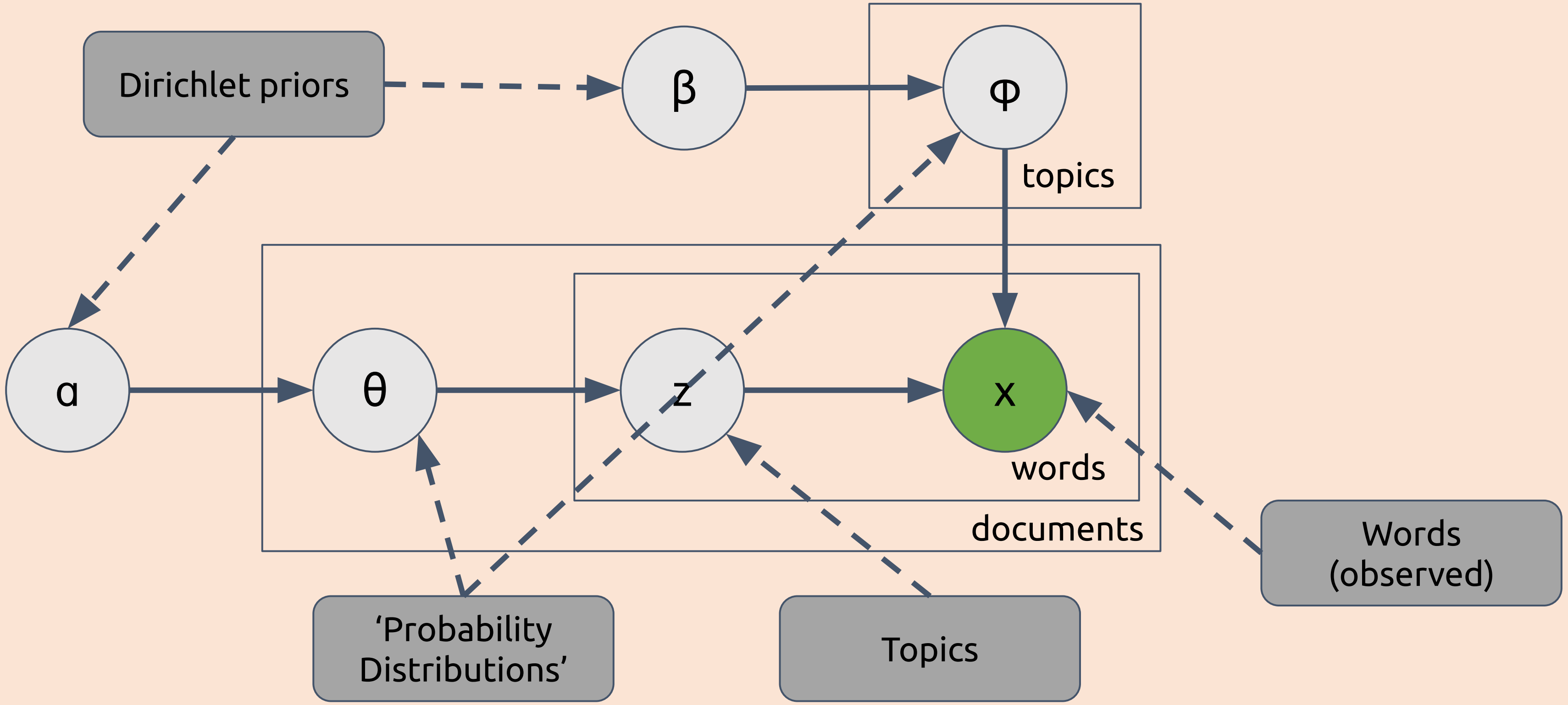
Per document 'topic' variable

Topic Models



Per document and per word ‘topic’ variable

Latent Dirichlet Allocation



$$P(X, Z, \Theta, \Phi; A, B) = \prod_i p(\phi_i; \beta) \prod_j p(\theta_j; \alpha) \prod_t p(z_{j,t}; \theta_j) p(x_{i,t} | z_{j,t}; \phi_i)$$

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PCFGs extends CFGs by adding weights to each production
The best parse tree can be found in cubic time
PCFGs have problems
- Cannot capture non-direct dependencies
- Cannot capture sibling dependencies
- Sometimes, cannot distinguish unlike trees

Lexicalized PCFGs fix these issues by adding a head word to each non-terminal
Dependency Grammars instead incorporate generalized links between words

Lab of this Week

Exercises on probabilistic parsing using NLTK

QA