Special Topics in Natural Language Processing

CS698O

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Lecture 15: Parsing 1
Feb 7, 2020

Context Free Grammar (CFG)

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$$Nominal \rightarrow Noun \mid Nominal Noun$$

$$Det \rightarrow a$$

$$Det \rightarrow the$$

$$Noun \rightarrow flight$$

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  - Lexicon contains words and ***symbols*** in the language

Context Free Grammar (CFG)

Symbols

- Terminal
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- Non-Terminal
  - Clustering or generalization of terminals (e.g. NP, POS, etc.)

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$$\textbf{Non-Terminal} \rightarrow \textbf{Terminal} \mid \textbf{Non-Terminal}$$

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$$Noun \rightarrow flight$$

Why CFG?

- CFG can be used for generating sentences
- CFG can be used for assigning structure to a sentence

GENERATION USING CFG

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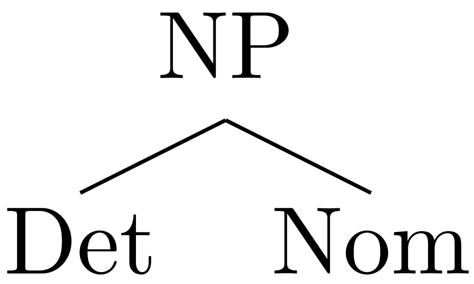
NP

1. Start with a NP

GENERATION USING CFG



1. Start with a NP
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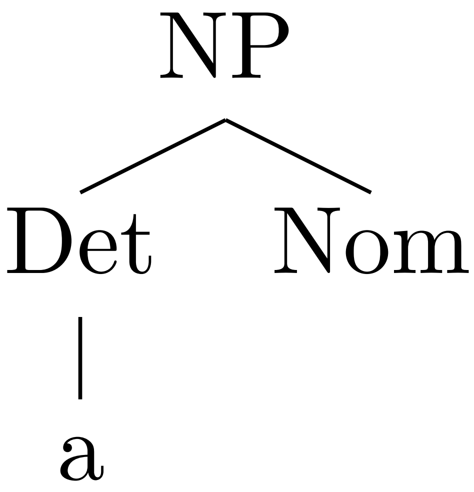

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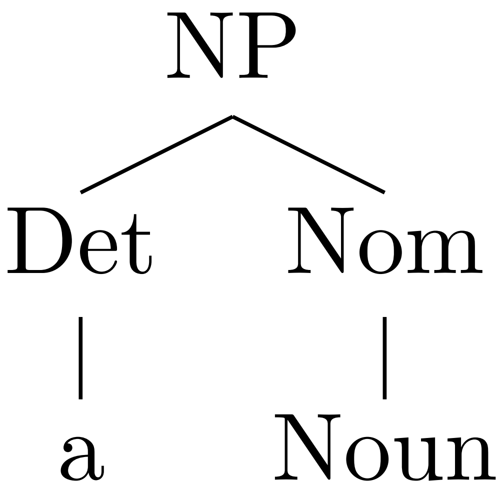

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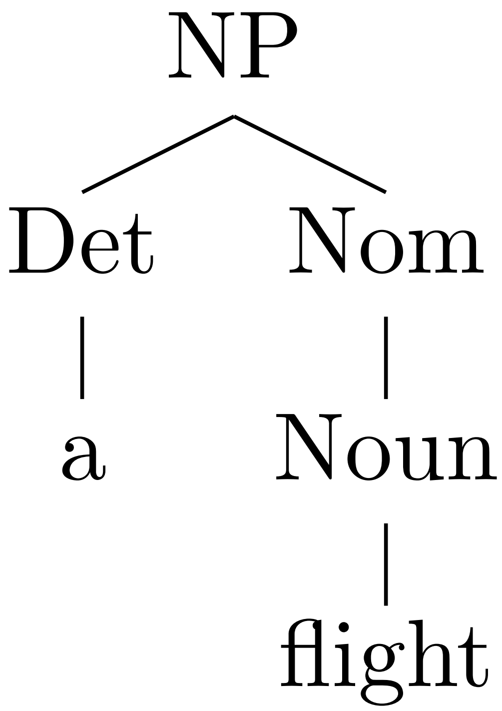

1. Start with a NP
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3. Use rule 4: Det → *a*
4. Use rule 3: Nom → Noun
5. Use rule 6: Noun → *flight*

CFG: BRACKETTED NOTATION

$[_{S}\ [_{NP}\ [_{Pro}\ \text{I}]\ ]\ [_{VP}\ [_{V}\ \text{prefer}]\ [_{NP}\ [_{Det}\ \text{a}]\ [_{Nom}\ [_{N}\ \text{morning}]\ [_{Nom}\ [_{N}\ \text{flight}]]]]]]$

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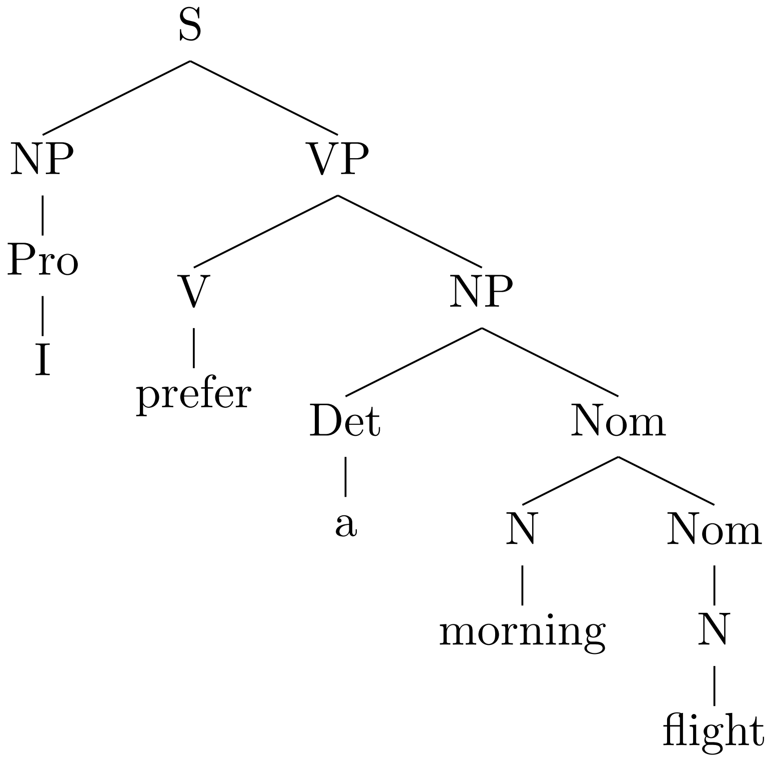

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- R is a finite set of rules of the form $X \rightarrow Y_1, \ldots, Y_n$,

  where $X \in N,\ n \geq 0$, and $Y_i \in (N \cup \Sigma)\ for\ i = 1, 2, \ldots, n$

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  where $X \in N,\ n \geq 0$, and $Y_i \in (N \cup \Sigma)\ for\ i = 1, 2, \ldots, n$
- $S \in N$ is a distinguished start symbol.

CFG: EXAMPLE

$S = \texttt{S}$

$N = \{\texttt{S, NP, VP, PP, DT, Vi, Vt, NN, IN}\}$

$\Sigma = \{\texttt{sleeps, saw, woman, telescope, dog man, the, with, in}\}$

$R =$

S → NP VP
VP → Vi VP → Vt NP VP → VP PP
NP → DT NN NP → NP PP
PP → IN NP

Vi → sleeps Vt → saw
NN → man NN → woman NN → telescope NN → dog
DT → the
IN → with IN → in

LEFT MOST DERIVATION

Given a context free grammar G,

a left most derivation is a sequence of strings $s_1, s_2, \ldots, s_n$

where,

- $s_1 = \mathtt{S}$ i.e., s_1 consists of a single element, the start symbol
- $s_n = \Sigma^*,$ i.e. s_n is made up of terminal symbols only
- Each s_i for $i = 2...n$ is derived from $s_i - 1$

  by picking the left-most non-terminal X in $s_i - 1$

  and replacing it by some β where

  $X \to \beta$ is a rule in R

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$$s_1 = \mathrm{S}$$

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$$s_1 = \mathrm{S}$$
$$s_2 = \mathrm{NP}\ \ \mathrm{VP}$$

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$$s_1 = \mathrm{S}$$
$$s_2 = \mathrm{NP}\ \ \mathrm{VP}$$
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$s_1 = \text{S}$

$s_2 = \text{NP VP}$

$s_3 = \text{DT NN VP}$

$s_4 = \text{the NN VP}$

LEFT MOST DERIVATION

S $\rightarrow$ NP VP
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NP $\rightarrow$ DT NN NP $\rightarrow$ NP PP
PP $\rightarrow$ IN NP

Vi $\rightarrow$ sleeps Vt $\rightarrow$ saw
NN $\rightarrow$ man NN $\rightarrow$ woman NN $\rightarrow$ telescope NN $\rightarrow$ dog
DT $\rightarrow$ the
IN $\rightarrow$ with IN $\rightarrow$ in

$$s_1 = \text{S}$$
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$$s_3 = \text{DT NN VP}$$
$$s_4 = \text{the NN VP}$$
$$s_5 = \text{the man VP}$$

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$$s_6 = \texttt{the man Vi}$$

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$s_7 = \text{the man sleeps}$

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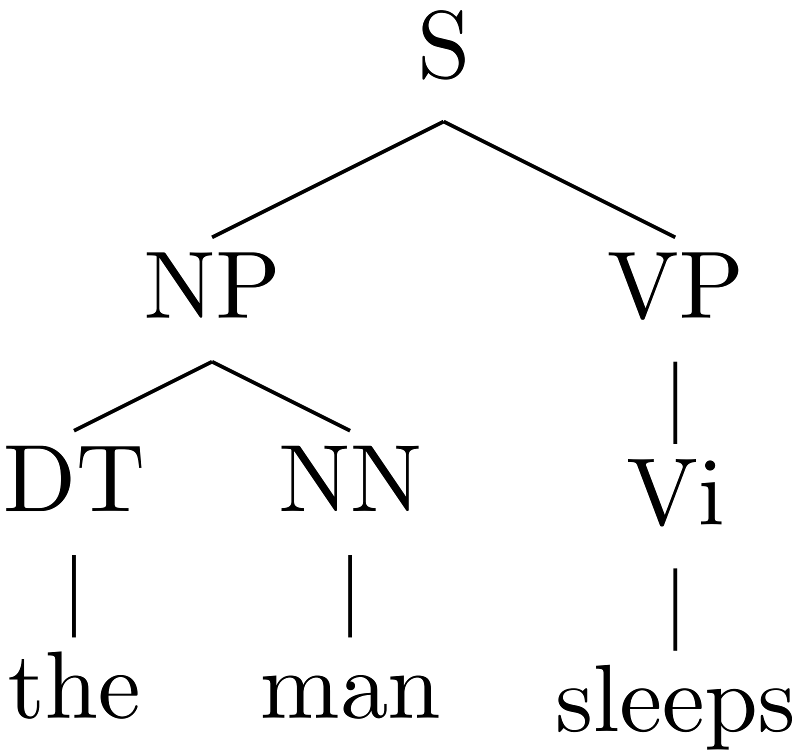

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CFG LANGUAGE

Each left most derivation of CFG G results in $s_n \in \Sigma^*$,
s_n is called *Yield* of the derivation

A string $s \in \Sigma^*$ is said to be in the *language* defined by the CFG, if there is at least one derivation whose yield is s

AMBIGUITY

A string *s* is *ambiguous* under the CFG if there is more than one derivation with *s* as the yield

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the man saw the dog with the telescope

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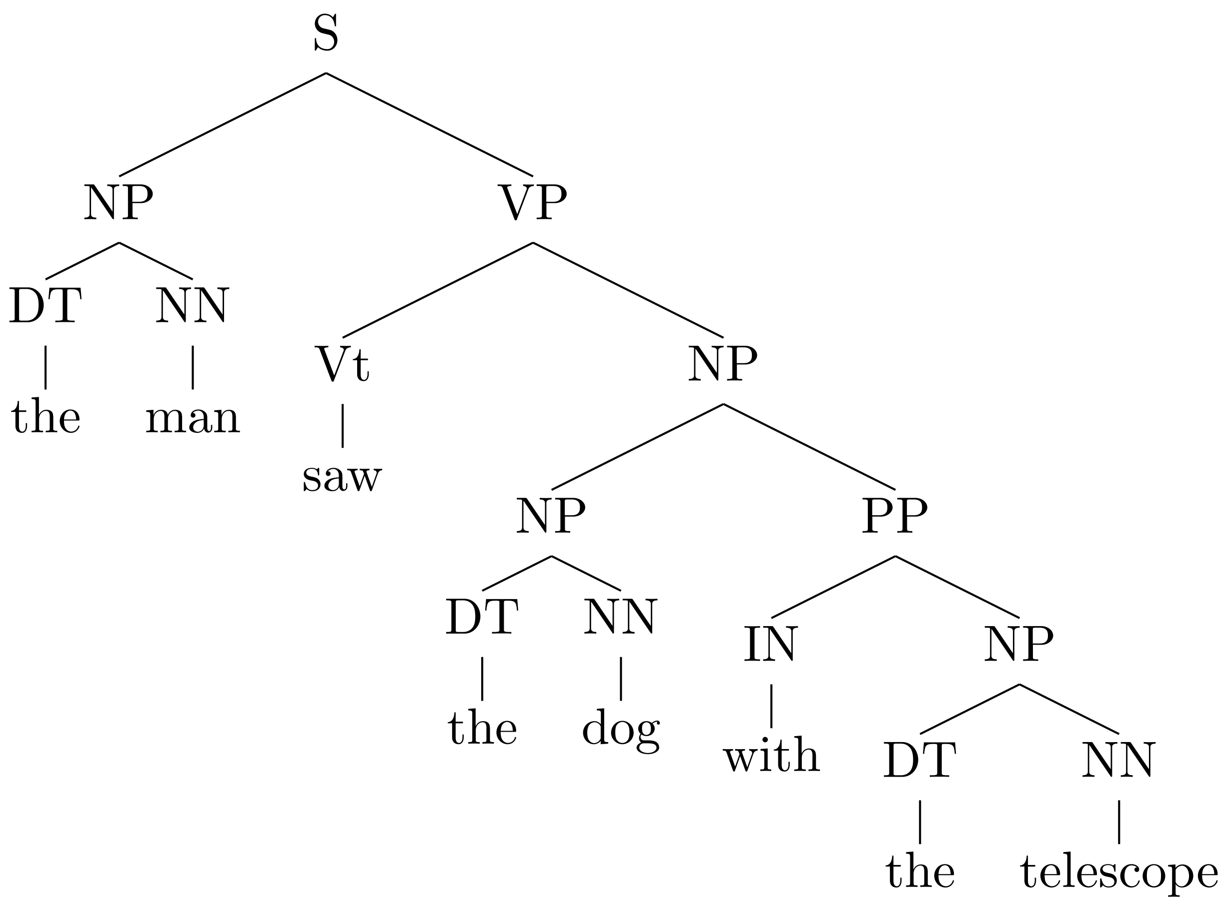
S
NP
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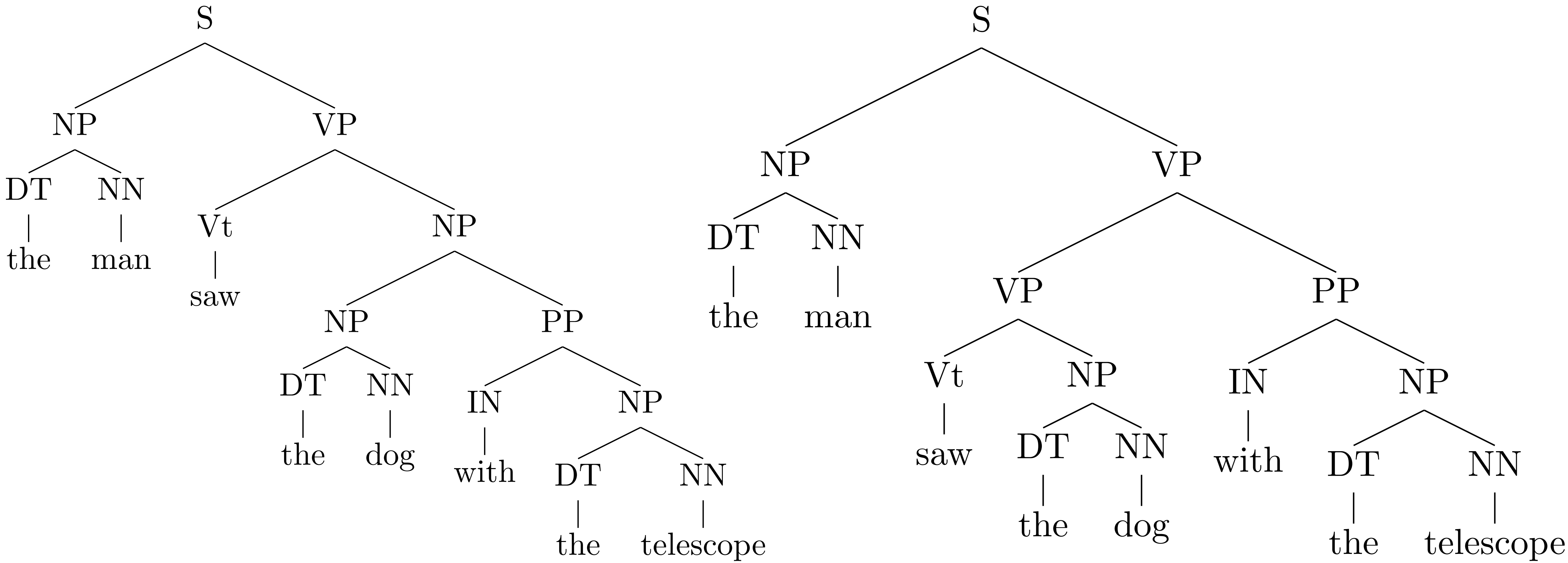
S
NP VP
DT NN Vt NP
the man saw
NP PP
DT NN IN NP
the dog with
DT NN
the telescope
S
NP VP
DT NN VP PP
the man
Vt NP IN NP
saw with
DT NN DT NN
the dog the telescope

AMBIGUITY

How many parse trees for the sentence?

She announced a program to promote safety in trucks and vans

DEFINITIONS

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A sentence is grammatical if $|\mathcal{T}_G| > 0$

PROBABILISTIC CFGs (PCFGs)

A PCFG consists of:

1. A context free grammar $G = (N, \Sigma, R, S)$
2. A parameter $q(\alpha \to \beta)$ for each rule $\alpha \to \beta \in R$

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$$\sum_{\substack{\alpha \rightarrow \beta \in R \\ \alpha = X \in N}} q(\alpha \rightarrow \beta) = 1$$

$$q(\alpha \rightarrow \beta) \geq 0 \; \forall \; \alpha \rightarrow \beta \in R$$

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Given a parse tree $t \in \mathcal{T}_G$ containing rules $\alpha_1 \rightarrow \beta_1, \alpha_2 \rightarrow \beta_2, \ldots, \alpha_n \rightarrow \beta_n$

$$p_{\text{PCFG}}(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i)$$

PCFG EXAMPLE

$S = \mathtt{S}$

$N = \{\mathtt{S,NP,VP,PP,DT,}$
$\mathtt{Vi,Vt,NN,IN}\}$

$\Sigma = \{\mathtt{sleeps,\ saw,\ woman,}$
$\mathtt{telescope,\ dog}$
$\mathtt{man,\ the,\ with,\ in}\}$

S → NP VP	1.0
VP → Vi	0.3
VP → Vt NP	0.5
VP → VP PP	0.2
NP → DT NN	0.8
NP → NP PP	0.2
PP → IN NP	1.0

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Vt → saw	1.0
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NN → dog	0.5
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IN → with	0.6
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$$\sum_{\substack{\alpha \to \beta \in R: \\ \alpha = VP}} q(\alpha \to \beta) = ?$$

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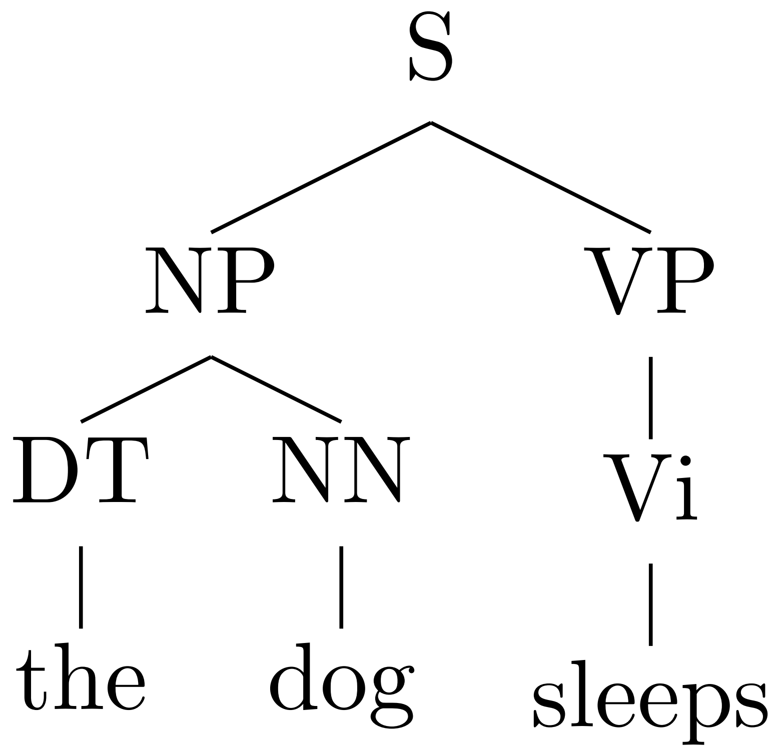

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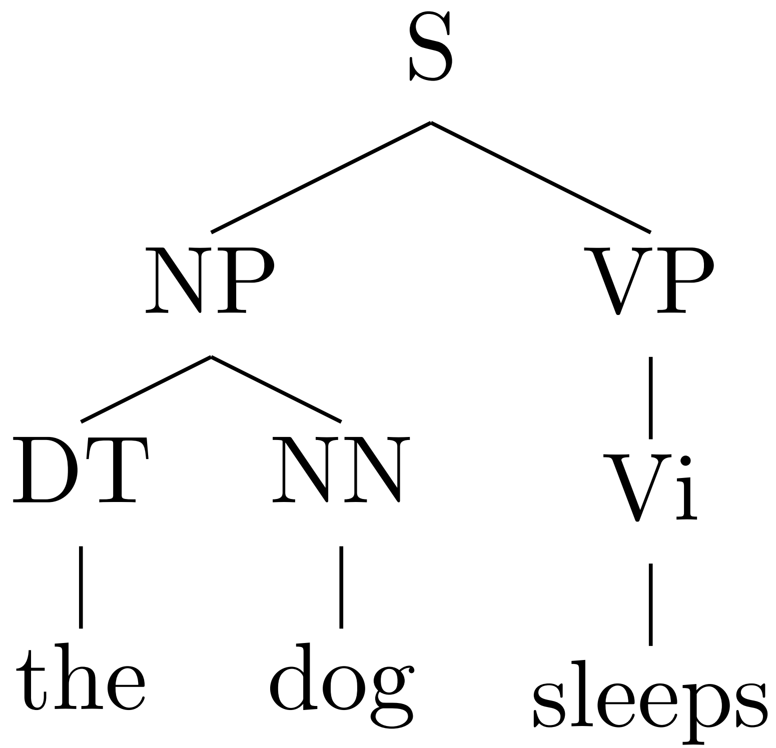

$$p(t) = ?$$

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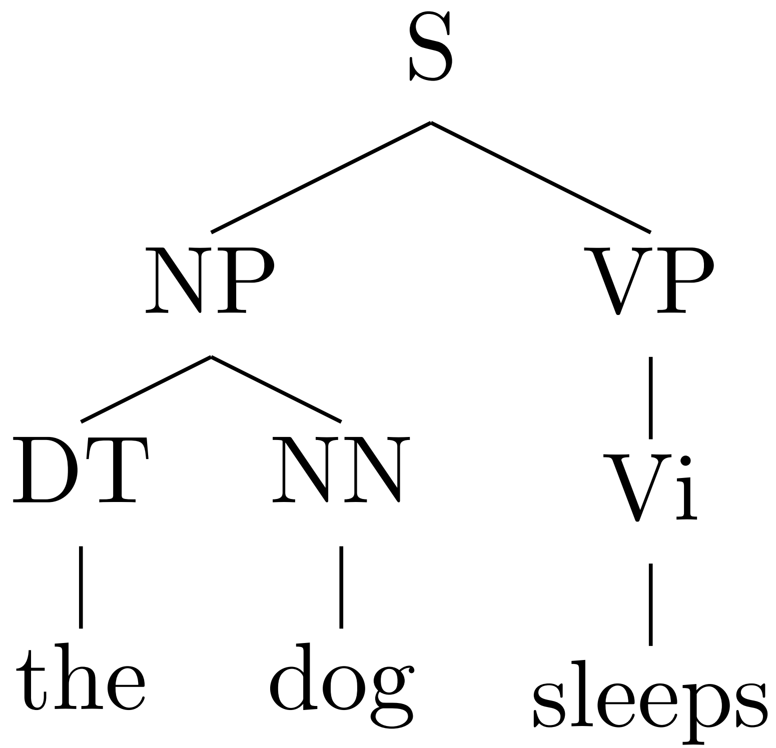

$$p(t) = q(\texttt{S} \to \texttt{NP VP}) \times q(\texttt{NP} \to \texttt{DT NN}) \times$$
$$q(\texttt{DT} \to \texttt{the}) \times q(\texttt{NN} \to \texttt{dog}) \times$$
$$q(\texttt{VP} \to \texttt{Vi}) \times q(\texttt{Vi} \to \texttt{sleeps})$$

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$$i = i + 1$$

PCFG

$$G = (N, \Sigma, R, S)$$

$$\sum_{\substack{\alpha \to \beta \in R \\ \alpha = X \in N}} q(\alpha \to \beta) = 1 \qquad\qquad q(\alpha \to \beta) \geq 0 \ \forall \ \alpha \to \beta \in R$$

Two Questions:

1. ***Learning Problem*** : How do we learn the parameters (probabilities)?
2. ***Decoding Problem***: Given a sentence *s* how do we find the most likely tree?

$$\underset{t \in \mathcal{T}_G(s)}{\operatorname{argmax}} \ p(t)$$

Summary

1. Languages can be modeled using grammar
2. CFG models the language in terms of constituents making use of rules and lexicon
3. A CFG can be modeled using $G = (N,\Sigma,R,S)$
4. Left most derivation using G *yields* strings in the language
5. CFG can help in resolving ambiguity
6. Probabilistic version of CFG (PCFG) helps in computationally and automatically parsing a language

References

1. Michael Collin’s NLP Lecture Notes: http://www.cs.columbia.edu/~mcollins/courses/nlp2011/notes/pcfgs.pdf

2. Chapter 12, Speech and Language Processing, Dan Jurafsky and James Martin