CS 784: Computational Linguistics
Lecture 13: Syntax: Constituency Parsing

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What is Syntax?

The cat near the children ____.

meow

meows

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The cat near the children ____.

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- Rules, principles, and processes that govern the sentence structure of a language.

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We use **grammar** to denote a formal object that represents the rules/principles/processes that determine sentence structure.

Subject, Verb, Object

Syntax determines the ordering of these components of a sentence.

Word order	English equivalent	Proportion of languages		Example languages
SOV	"Cows grass eat."	45%		Ancient Greek, Bengali, Burmese, Hindi/Urdu, Japanese, Korean, Latin, Persian, Sanskrit, Tamil, Telugu, Turkish, etc
SVO	"Cows eat grass."	42%		Chinese, English, French, Hausa, Hebrew, Arabic, Italian, Malay, Portuguese, Spanish, Swahili, Thai, Vietnamese, etc
VSO	"Eat cows grass."	9%		Biblical Hebrew, Classical Arabic, Filipino, Ge'ez, Irish, Māori, Tuareg-Berber, Welsh
VOS	"Eat grass cows."	3%		Car, Fijian, Malagasy, Q'eqchi', Terêna
OVS	"Grass eat cows."	1%		Hixkaryana, Urarina
OSV	"Grass cows eat."	0%		Tobati, Warao

Frequency distribution of word order in languages surveyed by Russell S. Tomlin in the 1980s[1][2] (v·t·e)

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Hanh and Xu (PNAS 2022): Information-theoretic justification on word orders.

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Focuses on **constituent relations**.

Informal understanding: sentences have hierarchical structure.

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A sentence is made up of two pieces:

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A sentence is made up of two pieces:

- Subject, typically a noun phrase (NP).
- Predicate, typically a verb phrase (VP).

NPs and VPs are made up of smaller pieces:

- `a cat = (a + cat)`
- `walked to the park = (walk + (to + (the + park) ) )`

Each parenthesized phrase is a constituent in the constituent parse.

Constituency Test

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- If the constructed sentence looks good (to native speakers), we find some positive evidence about constituency.

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Drunks could put off the customers.
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What are the possible constituents and why?

Coordination Test

Coordinate the candidate constituent with something else.

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- `Drunks [could] and [would] put off the customers.`

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- `* Drunks could and would put [off the] and […] customers.`

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Caveat: constituency tests are positive evidences but not necessary conditions.

Topicalization Test [1]

Move the candidate constituent to the front.

Modal adverbs can be added to improve naturalness.

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[1] Topicalization is a mechanism of syntax that establishes an expression as the sentence or clause topic by having it appear at the front of the sentence or clause (as opposed to in a canonical position later in the sentence).

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- …and `[the customers], drunks certainly could put off.`

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Deletion Test

Delete the span of interest.

Word orders can be changed to improve naturalness.

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Drunks could put off the customers in the bar.
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- `Drunks could put off the customers [`~~`in the bar`~~`].`

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- `Drunks could put off the customers [~~in the bar~~].`
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Substitution Test

Substitute the candidate constituent with the appropriate proform (pronoun/proverb/etc.).

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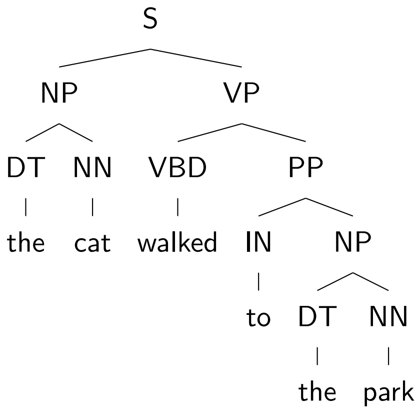
Being a constituent does not necessitate passing all tests.

But if a group of words is a constituent, it should pass at least one test.

Constituency Parsing as Bracketing

Which spans are constituents in a sentence?



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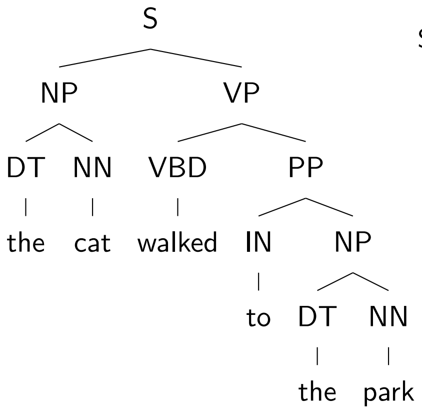

$S \rightarrow \quad$ (S NP VP)

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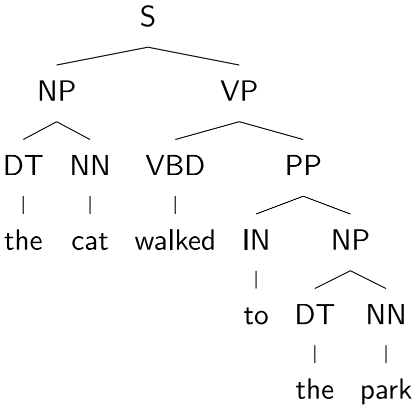

$$
\begin{aligned}
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&\rightarrow \text{(S (NP DT NN) VP)}
\end{aligned}
$$

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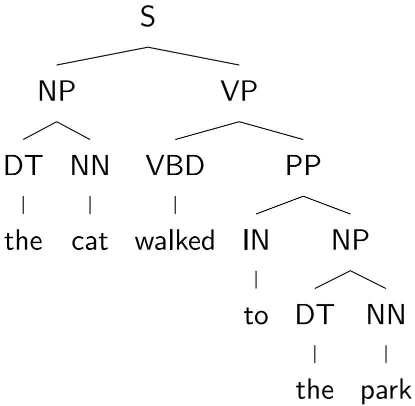

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&\rightarrow \quad \text{(S (NP DT NN) VP)} \\
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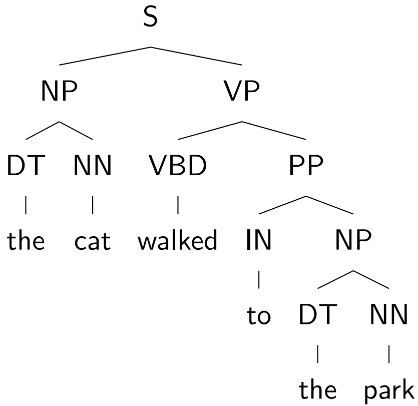
Constituency Parsing as Bracketing

Which spans are constituents in a sentence?



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(S
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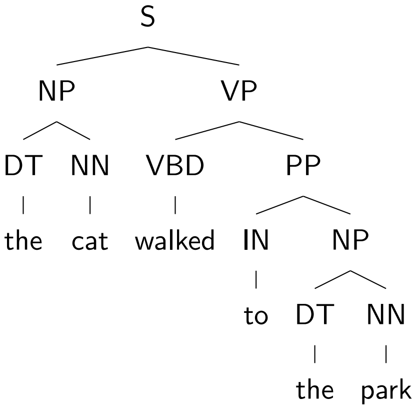

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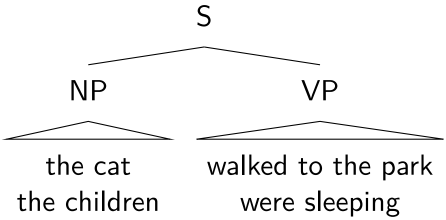
The brackets and trees are mutually translatable.

Labels as Syntactic Substitutability



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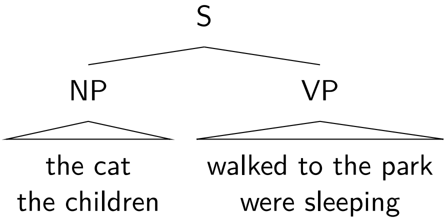
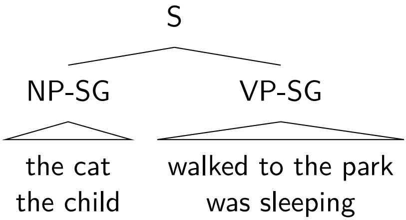
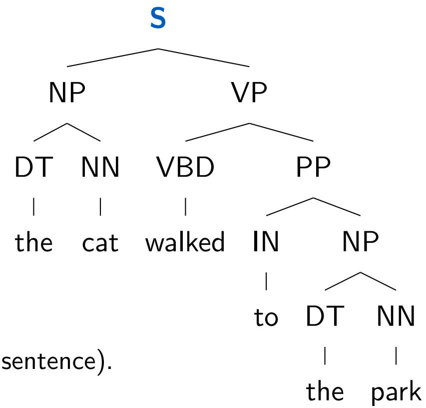


Constraints (e.g., singular/plural labels) are necessary to ensure grammaticality.



Types of Nodes



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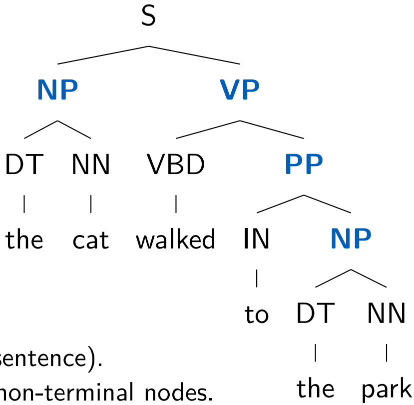

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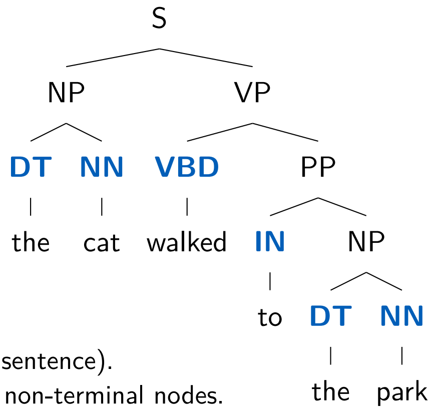

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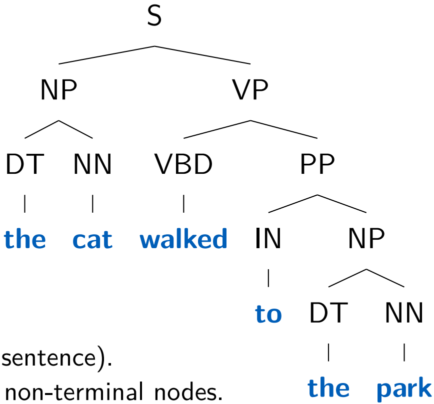

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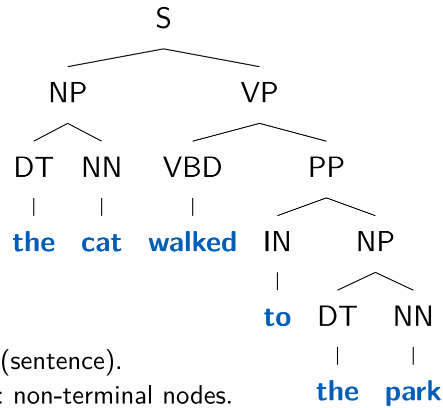

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The Penn treebank tagset: `https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html`

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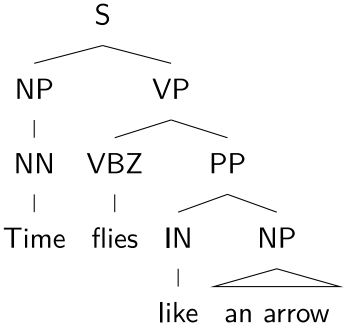
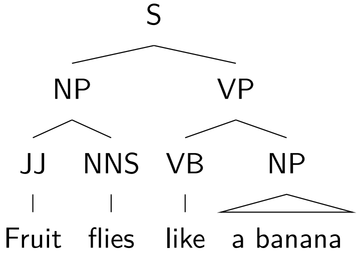
Caveat: There is room for ambiguity from the head concept above—in practice, Magerman (1995) and Collins (1999) propose head rules written by hand.

Syntactic Ambiguities

Time flies like an arrow.

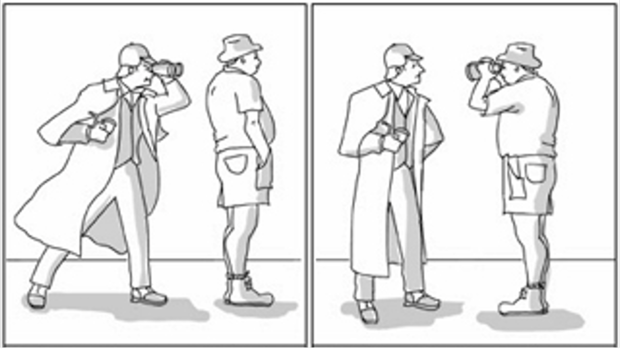


Fruit flies like a banana.



Syntactic Ambiguities: PP Attachment

Sherlock saw the man using binoculars.



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This coordination ambiguity has been a major issue of some neuro-symbolic models in language-based robot navigation (Mao et al., 2021).

Syntactic Ambiguities: Noun Compound and Adjective-Noun Ambiguity

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Connecting to the real-world context is the key to (possibly) resolve the ambiguity.

Garden-Path Sentences

What is (should be) the next token?

`The horse raced past the barn`

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Can be interpreted by explicitly drawing out the constituent parse tree.

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Context-free: the application of a rule does not depend on the context.

An Example CFG

- $\mathcal{N} = \{S, NP, VP\}$
- $\mathcal{T} = \{\text{a}, \text{cat}, \text{meows}\}$
- $\mathcal{R} =$ the set containing the following rules:
  - $S \rightarrow NP\ VP$
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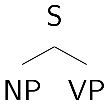

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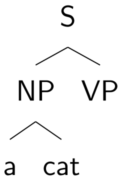

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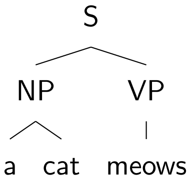

Weighted Context-Free Grammars

A **weighted context-free grammar** (WCFG) is a tuple $(\mathcal{N}, \mathcal{T}, \mathcal{R}, S, W)$.

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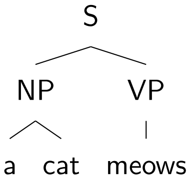

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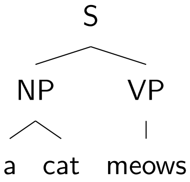

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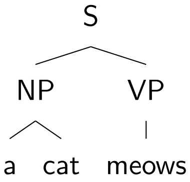

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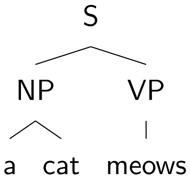

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Check out Hale (2003) for more!

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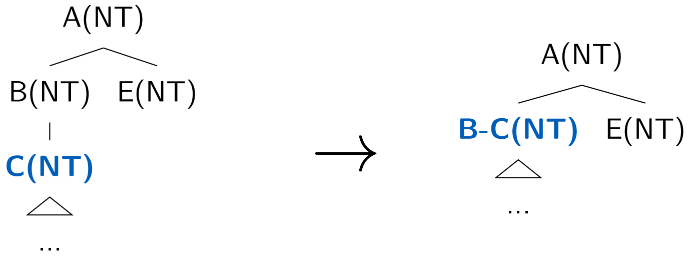

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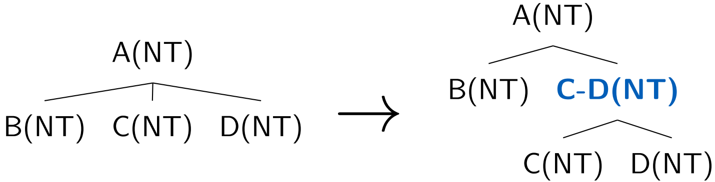

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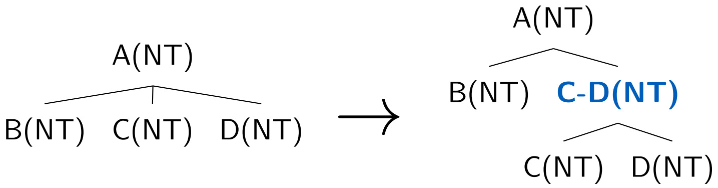

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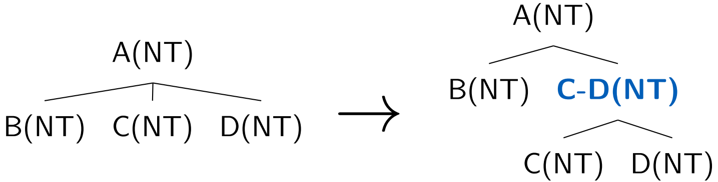

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It's provable that any CFG can be converted to an equivalent CFG in Chomsky normal form.

Constituency Parsing as an NLP Task

Given a sentence s, output its constituency parse tree.

$$\mathrm{parse}(s) = \arg\max_{\mathcal{Y}} \mathrm{score}(s, \mathcal{Y}; \boldsymbol{\Theta})$$

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Treebank: corpus of annotated parse trees.

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The Cocke–Kasami–Younger (CKY) algorithm is a dynamic programming algorithm for constituency parsing. Define

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Key idea: let $F[i, j, A]$ as the highest-possible score of a parse tree with non-terminal A spanning words i to j.

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$$F[i,j,A] = \max_{\substack{A \to B\ C \\ k \in [i,j-1]}} \{F[i,k,B] + F[k+1,j,C] + \log P_{\Theta}(A \to B\ C)\}$$

Edge cases: $F[i,i,A] = \log P_{\Theta}(A \to w_i)$ for (pre-)terminal rules.

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Problem formulation: given an input sentence, we score all $n(n-1)/2$ possible spans for each non-terminal label, and use CKY to find the best-scoring parse tree.

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Training objective: encourage the ground-truth tree to have higher score than all other trees (see Kitaev and Klein, 2018).

$$\max_{\boldsymbol{\Theta}} \sum_{(s,\mathcal{Y})\in\mathcal{D}} \left(\sum_{(\ell,r)\in\mathcal{Y}} \text{score}(\ell, r; s, \boldsymbol{\Theta}) - \underbrace{\max_{\mathcal{Y}'} \sum_{(\ell,r)\in\mathcal{Y}'} \text{score}(\ell, r; s, \boldsymbol{\Theta})}_{\text{CKY algorithm}} \right)$$

Evaluation of Constituency Parsing

Bracketing F1 score: the harmonic mean of precision and recall of the bracketing.

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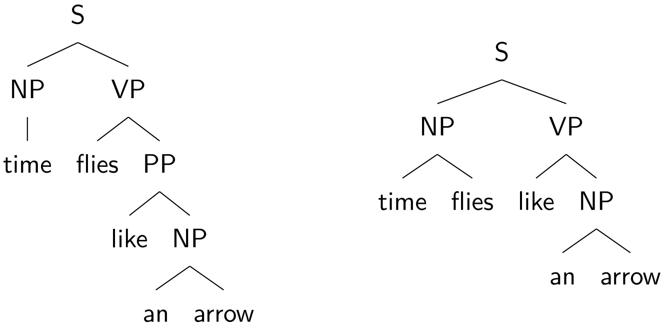

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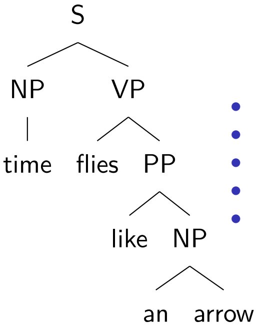

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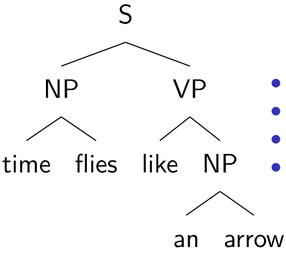

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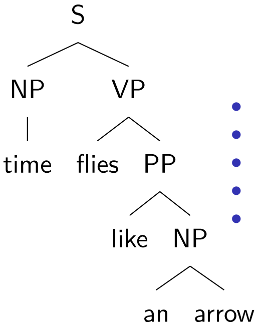

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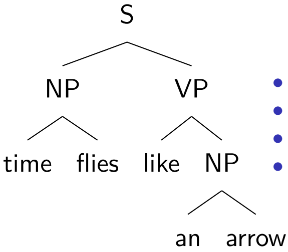

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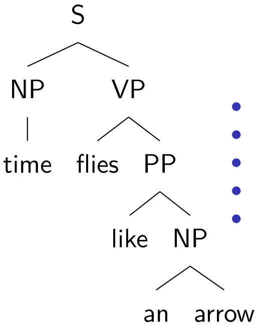

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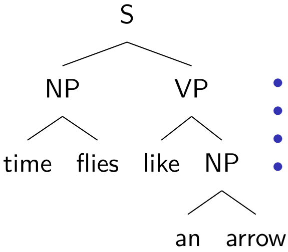

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$$\text{Precision} = \frac{2}{5} \quad \text{Recall} = \frac{2}{4} \quad F_1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = 0.44$$

Next

Syntax: Dependency Parsing