Natural Language Processing

Syntactic parsing

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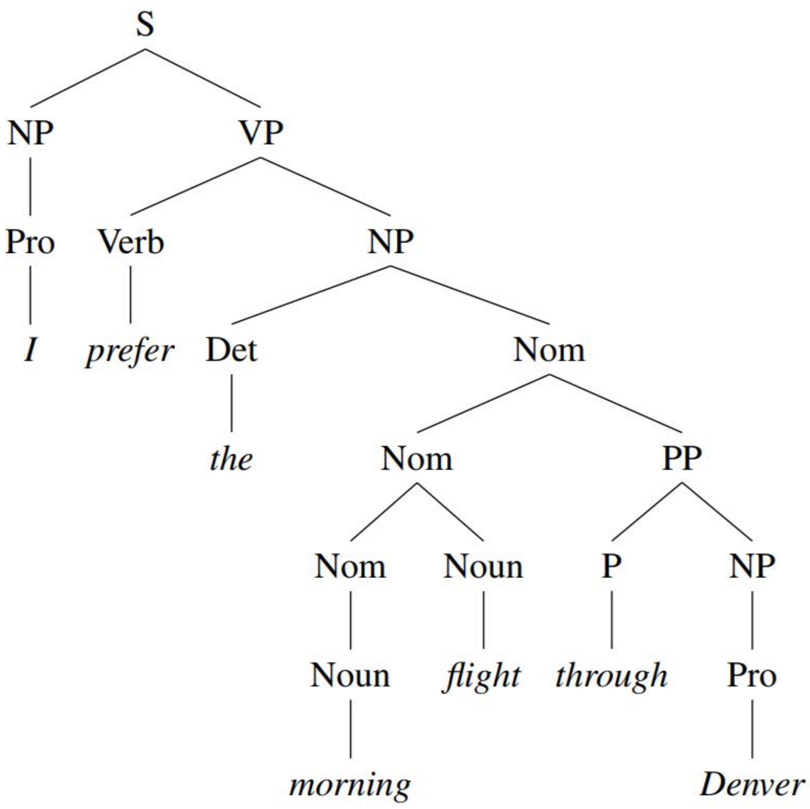
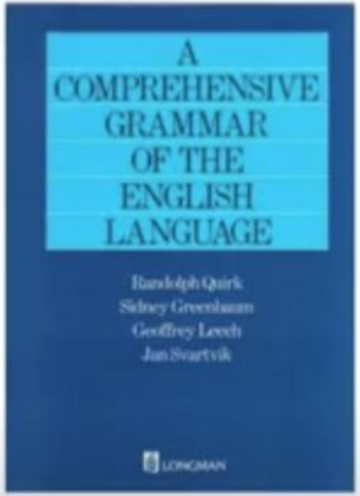
OF COMPUTER SCIENCE & ENGINEERING

Constituent (phrase-structure) representation



English grammar



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Shipping Weight: 4.6 pounds

Context Free Grammar (CFG)

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Grammar (CFG)

ROOT → S
S → NP VP
NP → DT NN
NP → NN NNS
NP → NP PP
VP → VBP NP
VP → VBP NP PP
PP → IN NP

Lexicon

NN → interest
NNS → raises
VBP → interest
VBZ → raises
…

Other grammar formalisms: LFG, HPSG, TAG, CCG…

CFGs

S

$$S \rightarrow NP\ VP$$

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

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

$$PP \rightarrow P\ NP$$

$$N \rightarrow girl$$
$$N \rightarrow telescope$$
$$N \rightarrow sandwich$$
$$PN \rightarrow I$$
$$V \rightarrow saw$$
$$V \rightarrow ate$$
$$P \rightarrow with$$
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$$D \rightarrow a$$
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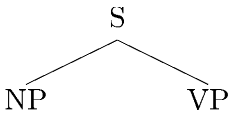
CFGs



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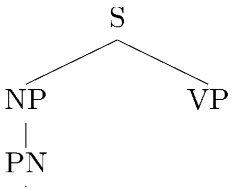

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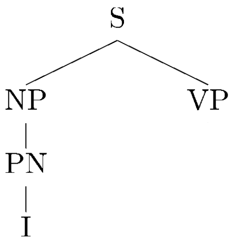

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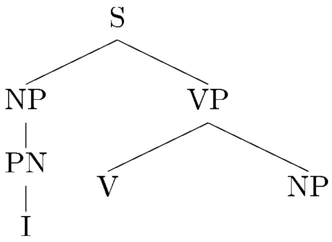

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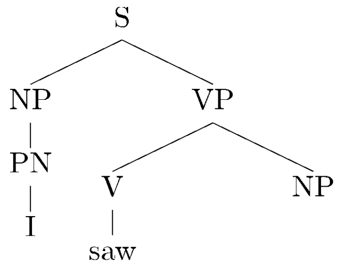

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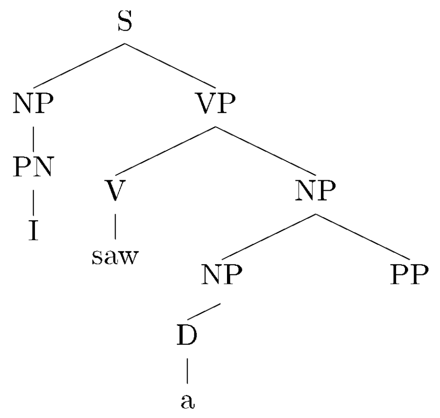

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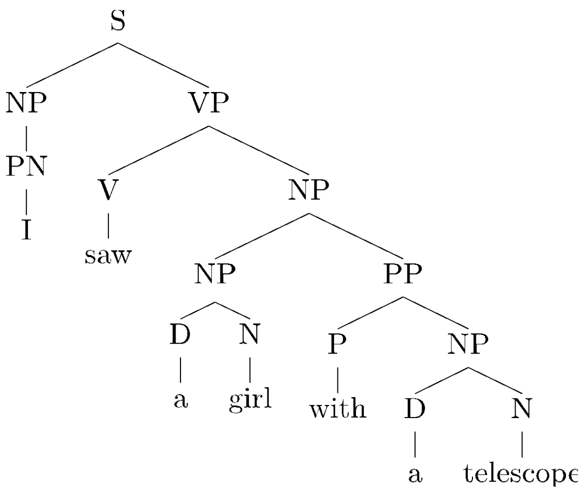

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Treebank Sentences

```
( (S (NP-SBJ The move)
     (VP followed
         (NP (NP a round)
             (PP of
                 (NP (NP similar increases)
                     (PP by
                         (NP other lenders))
                     (PP against
                         (NP Arizona real estate loans)))))
         ,
         (S-ADV (NP-SBJ *)
                (VP reflecting
                    (NP (NP a continuing decline)
                        (PP-LOC in
                                (NP that market))))))
     .))
```

Context-Free Grammars

- A context-free grammar is a 4-tuple <N, T, S, R>
  - N : the set of non-terminals
    - **Phrasal categories**: S, NP, VP, ADJP, etc.
    - **Parts-of-speech** (pre-terminals): NN, JJ, DT, VB
  - T : the set of terminals (the words)
  - S : the start symbol
    - Often written as ROOT or TOP
    - Not usually the sentence non-terminal S
  - R : the set of rules
    - Of the form $X \rightarrow Y_1\ Y_2\ \ldots\ Y_k$, with $X, Y_i \in N$
    - Examples: $S \rightarrow NP\ VP$, $VP \rightarrow VP\ CC\ VP$
    - Also called rewrites, productions, or local trees

An example grammar

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

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

$S = \{S\}$

$R:$

Called **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

$N \rightarrow girl$

$N \rightarrow telescope$

$N \rightarrow sandwich$

$PN \rightarrow I$

$V \rightarrow saw$

$V \rightarrow ate$

$P \rightarrow with$

$P \rightarrow in$

$D \rightarrow a$

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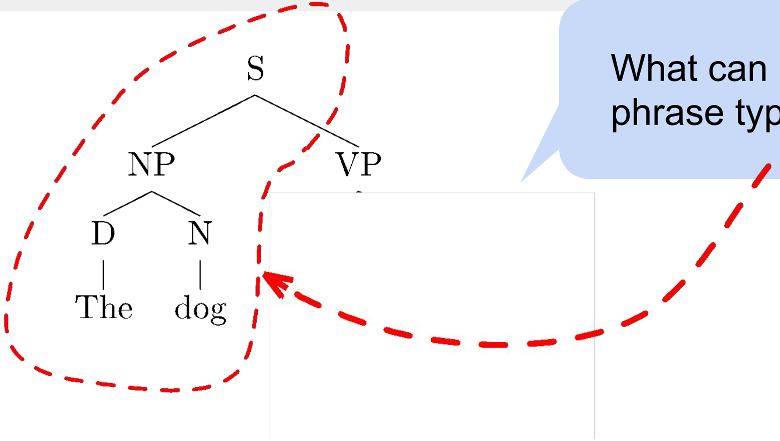
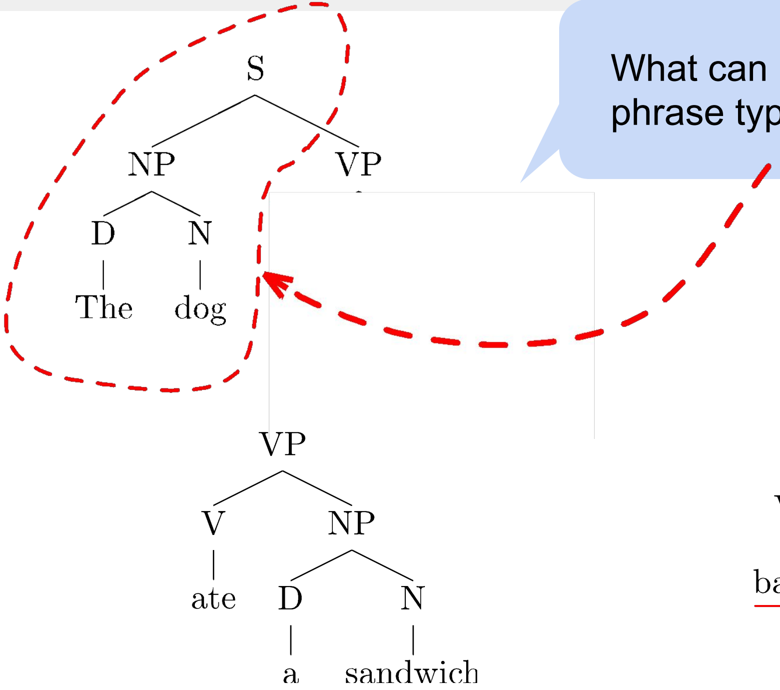
Why context-free?

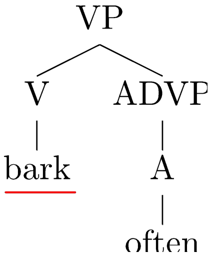


What can be a sub-tree is only affected by what the phrase type is (VP) but not the context

Why context-free?



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

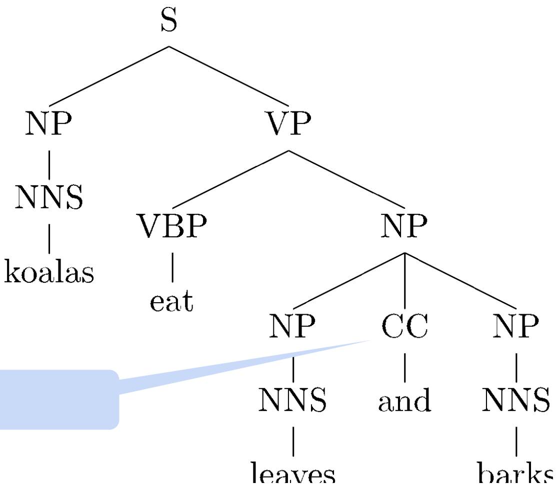


Not grammatical

Ambiguities

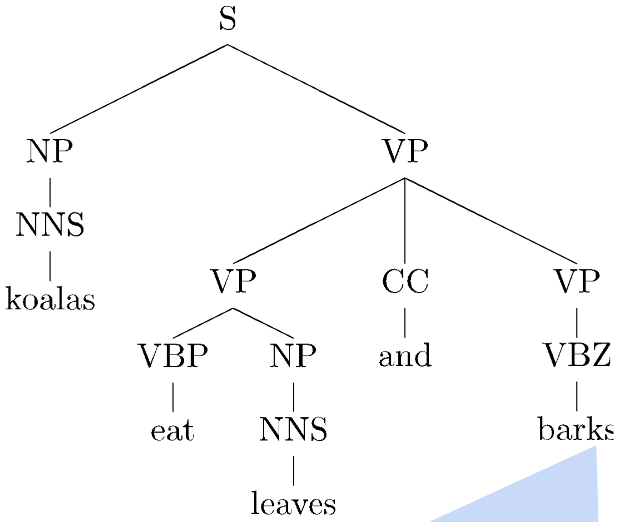
Coordination ambiguity

- Here, the coarse VP and NP categories cannot enforce subject-verb agreement in number resulting in the coordination ambiguity



Coordination

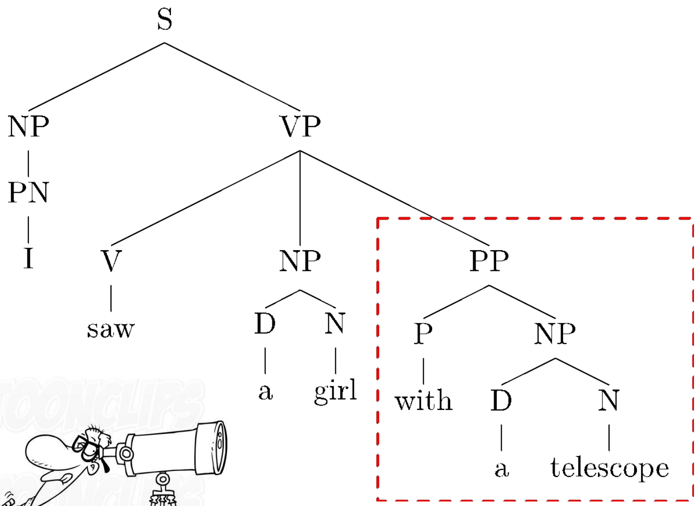
"Bark" can refer both to a noun or a verb

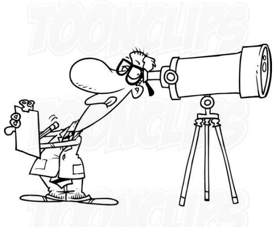


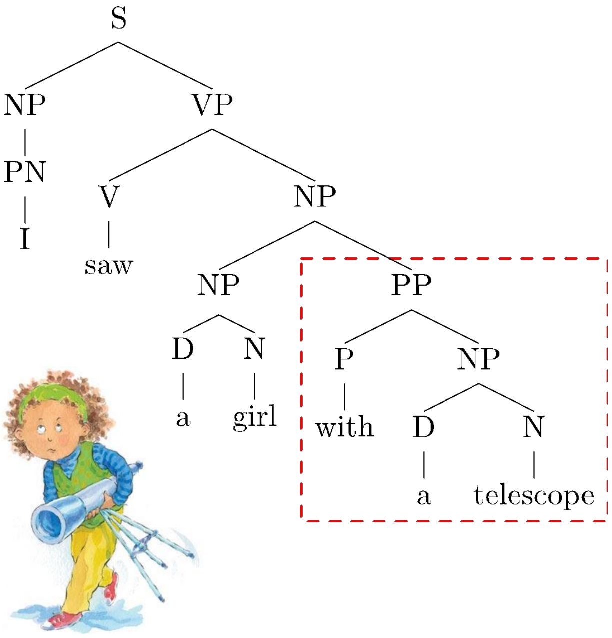
This tree would be ruled out if the context would be somehow captured (subject-verb agreement)

Why is parsing hard? Ambiguity

- Prepositional phrase attachment ambiguity







PP Ambiguity

Put the block in the box on the table in the kitchen

3 prepositional phrases, 5 interpretations:

- Put the block ((in the box on the table) in the kitchen)
- Put the block (in the box (on the table in the kitchen))
- Put ((the block in the box) on the table) in the kitchen.
- Put (the block (in the box on the table)) in the kitchen.
- Put (the block in the box) (on the table in the kitchen)

PP Ambiguity

Put the block in the box on the table in the kitchen

3 prepositional phrases, 5 interpretations:

- Put the block ((in the box on the table) in the kitchen)
- Put the block (in the box (on the table in the kitchen))
- …

A general case:

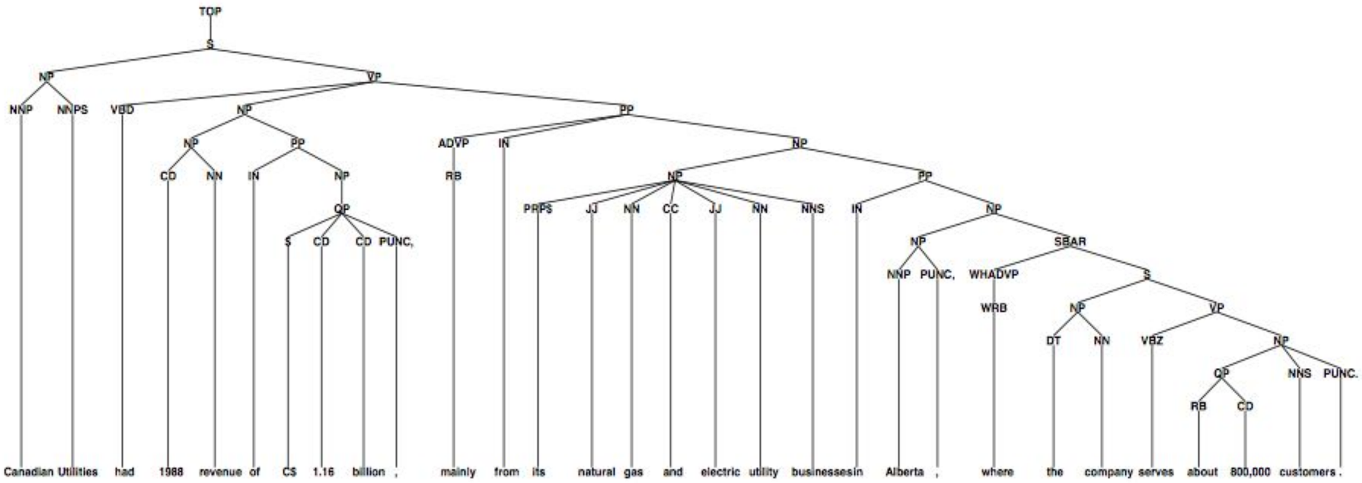
- ((()))   ()(())   ()()()   (())()   (()())

$$Cat_n = \binom{2n}{n} - \binom{2n}{n-1} \sim \frac{4^n}{n^{3/2}\sqrt{\pi}}$$

Catalan numbers

$$1, 2, 5, 14, 42, 132, 429, 1430, 4862, 16796, 58786, \ldots$$

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



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 .

[from Michael Collins slides]

Syntactic Ambiguities I

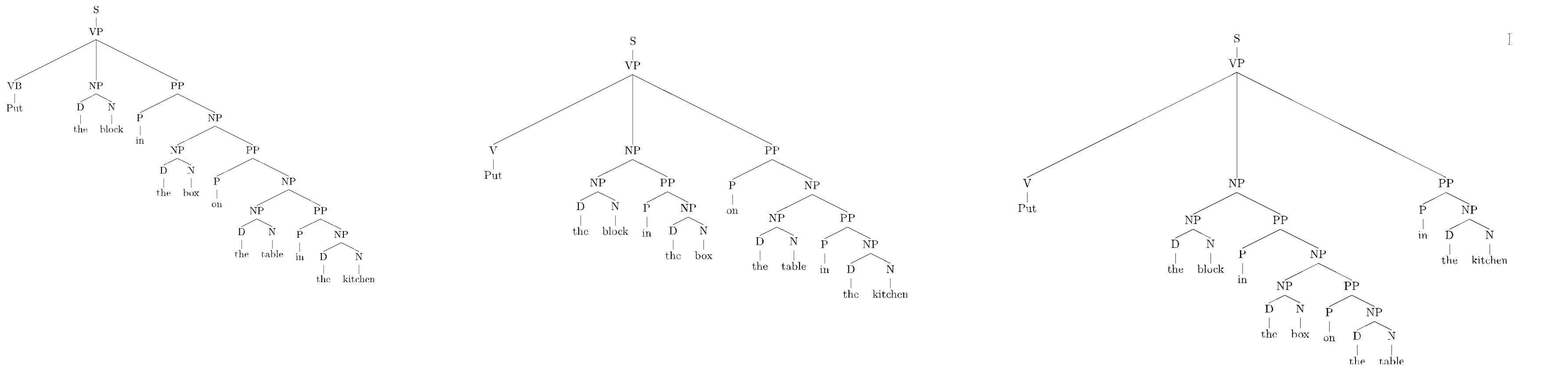
- Prepositional phrases:
  - They cooked the beans in the pot on the stove with handles.
- Particle vs. preposition:
  - The puppy tore up the staircase.
- Complement structures
  - The tourists objected to the guide that they couldn't hear.
    She knows you like the back of her hand.
- Gerund vs. participial adjective
  - Visiting relatives can be boring.
    Changing schedules frequently confused passengers.

Syntactic Ambiguities II

- Modifier scope within NPs
  - impractical design requirements
    plastic cup holder
- Multiple gap constructions
  - The chicken is ready to eat.
    The contractors are rich enough to sue.
- Coordination scope:
  - Small rats and mice can squeeze into holes or cracks in the wall.

How to Deal with Ambiguity?

- We want to score all the derivations to encode how plausible they are



Put the block in the box on the table in the kitchen

Probabilistic Context Free Grammar (PCFG)

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    - Examples: $S \rightarrow NP\ VP$, $VP \rightarrow VP\ CC\ VP$
    - Also called rewrites, productions, or local trees

- A PCFG adds:
  - A top-down production probability per rule $P(Y_1\ Y_2 \ldots Y_k \mid X)$

PCFGs

Associate probabilities with the rules : $p(X \rightarrow \alpha)$

$$\forall \;\; X \rightarrow \alpha \in R : \quad 0 \leq p(X \rightarrow \alpha) \leq 1$$

$$\forall X \in N : \quad \sum_{\alpha : X \rightarrow \alpha \in R} p(X \rightarrow \alpha) = 1$$

Now we can score a tree as a product of probabilities corresponding to the used rules

$S \rightarrow NP \;\; VP$	1.0	(NP A girl) (VP ate a sandwich)
$VP \rightarrow V$	0.2	
$VP \rightarrow V \;\; NP$	0.4	(VP ate) (NP a sandwich)
$VP \rightarrow VP \;\; PP$	0.4	(VP saw a girl) (PP with …)
$NP \rightarrow NP \;\; PP$	0.3	(NP a girl) (PP with ….)
$NP \rightarrow D \;\; N$	0.5	(D a) (N sandwich)
$NP \rightarrow PN$	0.2	
$PP \rightarrow P \;\; NP$	1.0	(P with) (NP with a sandwich)

$N \rightarrow girl$	0.2
$N \rightarrow telescope$	0.7
$N \rightarrow sandwich$	0.1
$PN \rightarrow I$	1.0
$V \rightarrow saw$	0.5
$V \rightarrow ate$	0.5
$P \rightarrow with$	0.6
$P \rightarrow in$	0.4
$D \rightarrow a$	0.3
$D \rightarrow the$	0.7

PCFGs

$S \rightarrow NP\ \ VP$ 1.0

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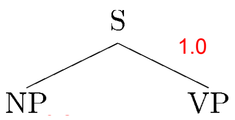
S

$p(T) =$

PCFGs



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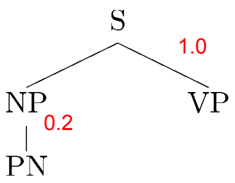
$$p(T) = 1.0 \times$$

PCFGs



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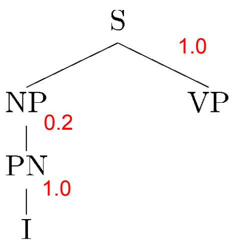
$$p(T) = 1.0 \times 0.2 \times$$

PCFGs



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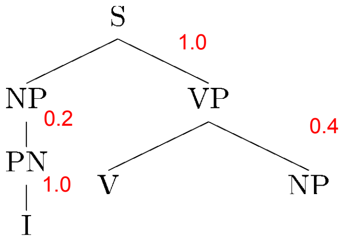
PCFGs



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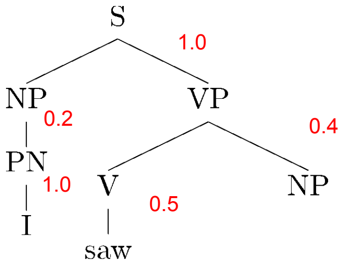

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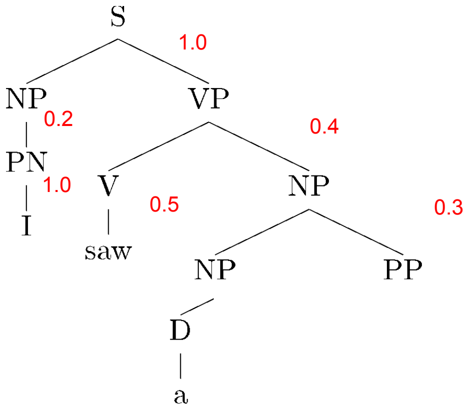

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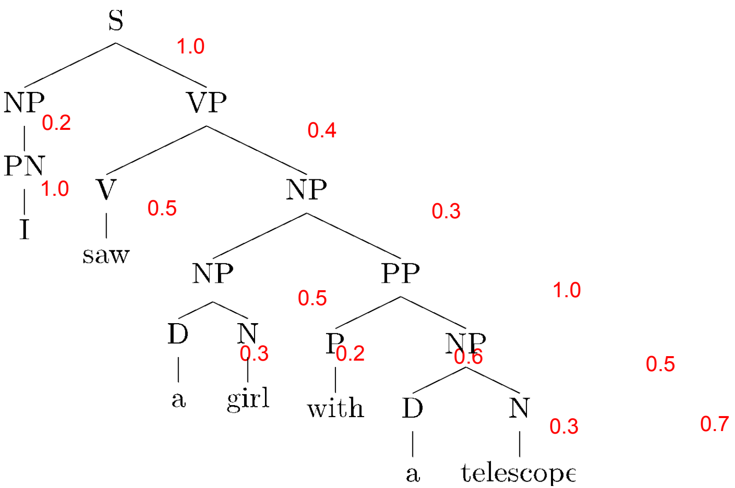
PCFGs



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$VP \rightarrow V \;\; NP$ 0.4

$VP \rightarrow VP \;\; PP$ 0.4

$NP \rightarrow NP \;\; PP$ 0.3

$NP \rightarrow D \;\; N$ 0.5

$NP \rightarrow PN$ 0.2

$PP \rightarrow P \;\; NP$ 1.0

$N \rightarrow girl$ 0.2

$N \rightarrow telescope$ 0.7

$N \rightarrow sandwich$ 0.1

$PN \rightarrow I$ 1.0

$V \rightarrow saw$ 0.5

$V \rightarrow ate$ 0.5

$P \rightarrow with$ 0.6

$P \rightarrow in$ 0.4

$D \rightarrow a$ 0.3

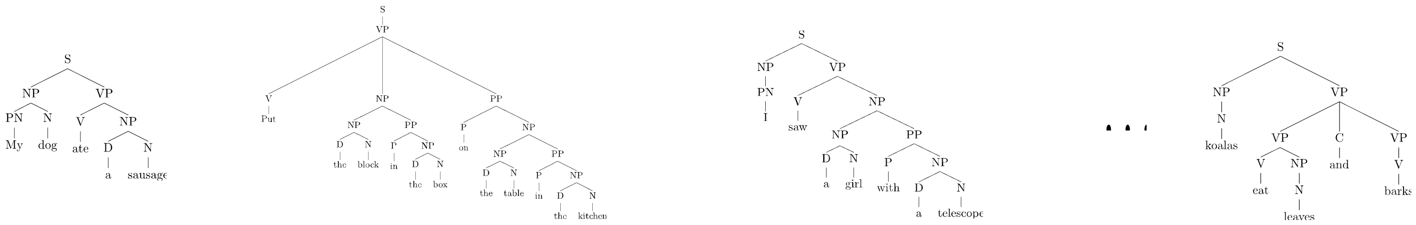
$D \rightarrow the$ 0.7

$$p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times 0.5 \times 0.3 \times$$
$$0.5 \times 0.3 \times 0.2 \times 1.0 \times 0.6 \times 0.5 \times 0.3 \times 0.7 \;\; = 2.26 \times 10^{-5}$$

PCFG Estimation

ML estimation

- A treebank: a collection sentences annotated with constituent trees



- An estimated probability of a rule (maximum likelihood estimates)

$$p(X \to \alpha) = \frac{C(X \to \alpha)}{C(X)}$$

The number of times the rule used in the corpus

The number of times the nonterminal X appears in the treebank

- Smoothing is helpful
  - Especially important for preterminal rules

Parsing evaluation

Parsing evaluation

- Intrinsic evaluation:
  - Automatic: evaluate against annotation provided by human experts (gold standard) according to some predefined measure
  - Manual: … according to human judgment

- Extrinsic evaluation: score syntactic representation by comparing how well a system using this representation performs on some task
  - E.g., use syntactic representation as input for a semantic analyzer and compare results of the analyzer using syntax predicted by different parsers.

Standard evaluation setting in parsing

- Automatic intrinsic evaluation is used: parsers are evaluated against gold standard by provided by linguists
  - There is a standard split into the parts:
    - training set: used for estimation of model parameters
    - development set: used for tuning the model (initial experiments)
    - test set: final experiments to compare against previous work

Automatic evaluation of constituent parsers

- Exact match: percentage of trees predicted correctly
- Bracket score: scores how well individual phrases (and their boundaries) are identified

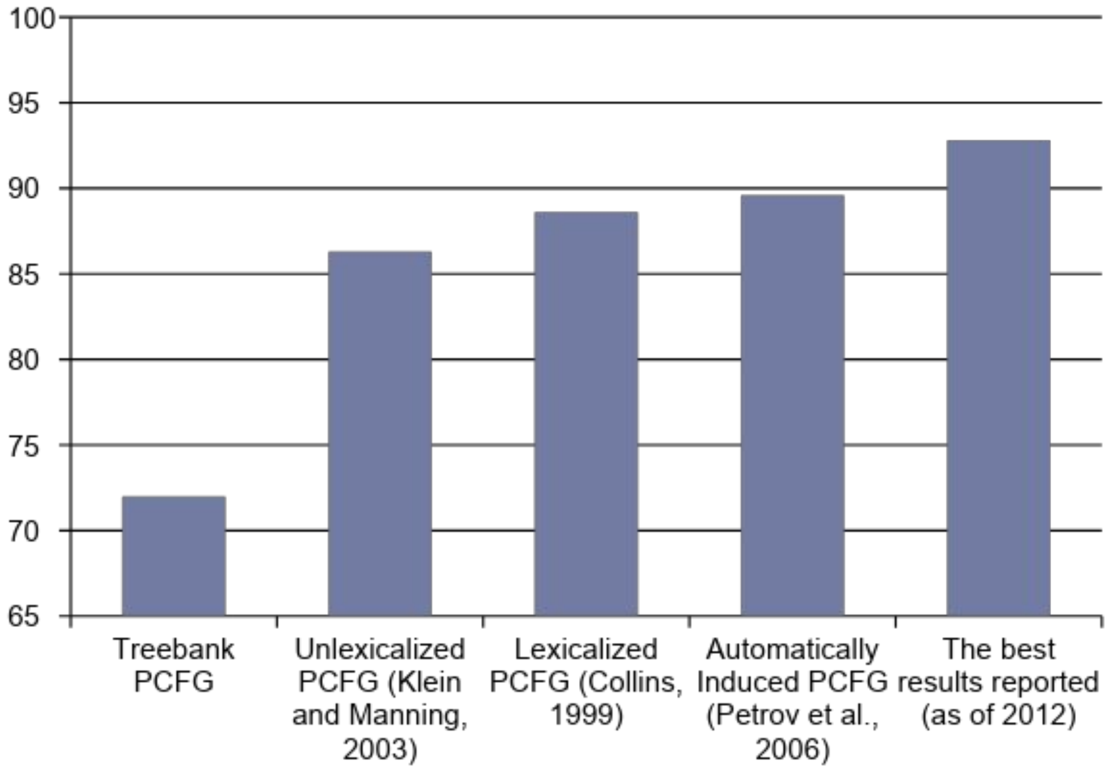
The most standard measure; we will focus on it

Brackets scores

Subtree signatures for CKY

- The most standard score is bracket score
- It regards a tree as a collection of brackets: $[min, max, C]$
- The set of brackets predicted by a parser is compared against the set of brackets in the tree annotated by a linguist
- Precision, recall and F1 are used as scores

Preview: F1 bracket score



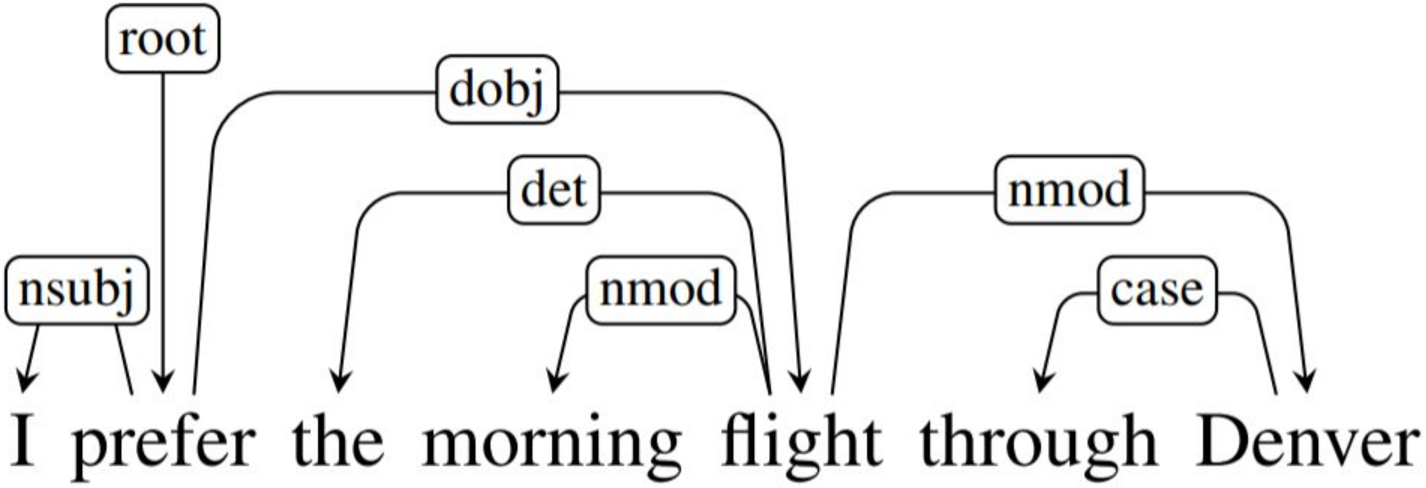
CKY Parsing

- Dynamic programming algorithm
- Not covered in lectures but see slides from the previous lecture if you are interested in learning more

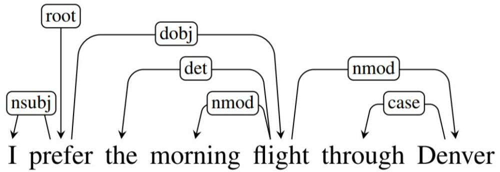
Dependency Treebanks

- the major English dependency treebanks converted from the WSJ sections of the PTB (Marcus et al., 1993)
- OntoNotes project (Hovy et al. 2006, Weischedel et al. 2011) adds conversational telephone speech, weblogs, usenet newsgroups, broadcast, and talk shows in English, Chinese and Arabic
- annotated dependency treebanks created for morphologically rich languages such as Czech, Hindi and Finnish, eg Prague Dependency Treebank (Bejcek et al., 2013)
- http://universaldependencies.org/
  - 150 treebanks, 90 languages

Dependency representation



Dependency representation



- A dependency structure can be defined as a directed graph G, consisting of
  - a set V of nodes – vertices, *words, punctuation, morphemes*
  - a set A of arcs – directed edges,
  - a linear precedence order < on V (word order).
- Labeled graphs
  - nodes in V are labeled with word forms (and annotation).
  - arcs in A are labeled with dependency types
  - $L = \{l_1, \ldots, l_{|L|}\}$ is the set of permissible arc labels;
  - Every arc in A is a triple (i,j,k), representing a dependency from w_i to w_j with label l_k.

Conversion from constituency to dependency

- Xia and Palmer (2001)
  - mark the head child of each node in a phrase structure, using the appropriate head rules
  - make the head of each non-head child depend on the head of the head-child

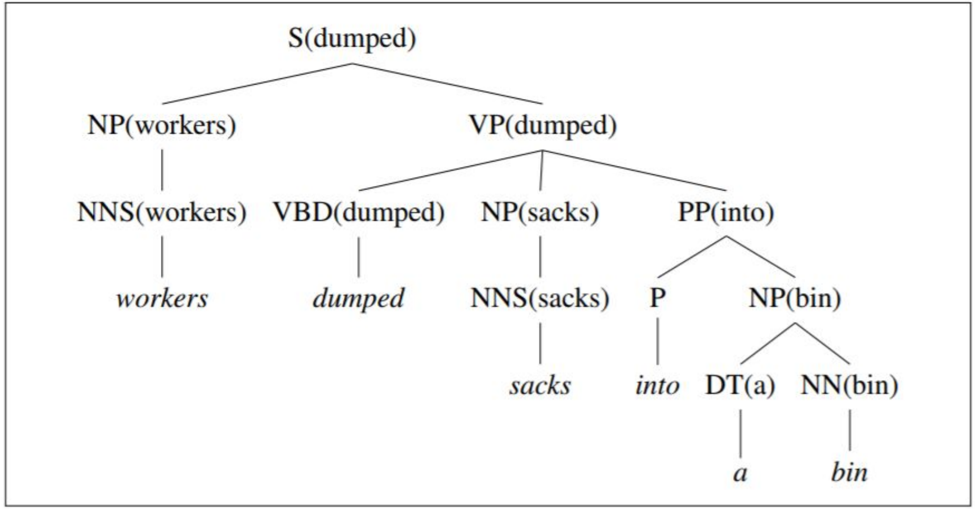


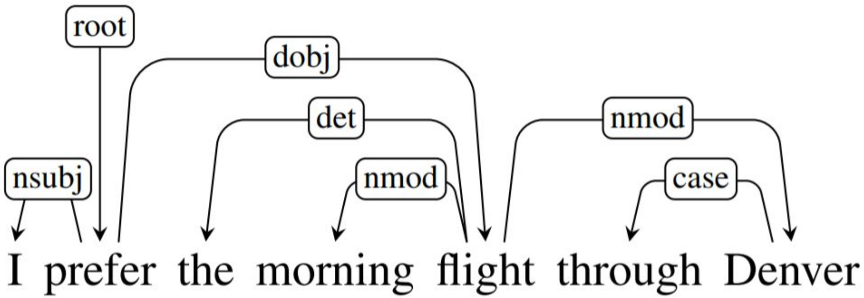
Figure 10.11 A lexicalized tree from Collins (1999).

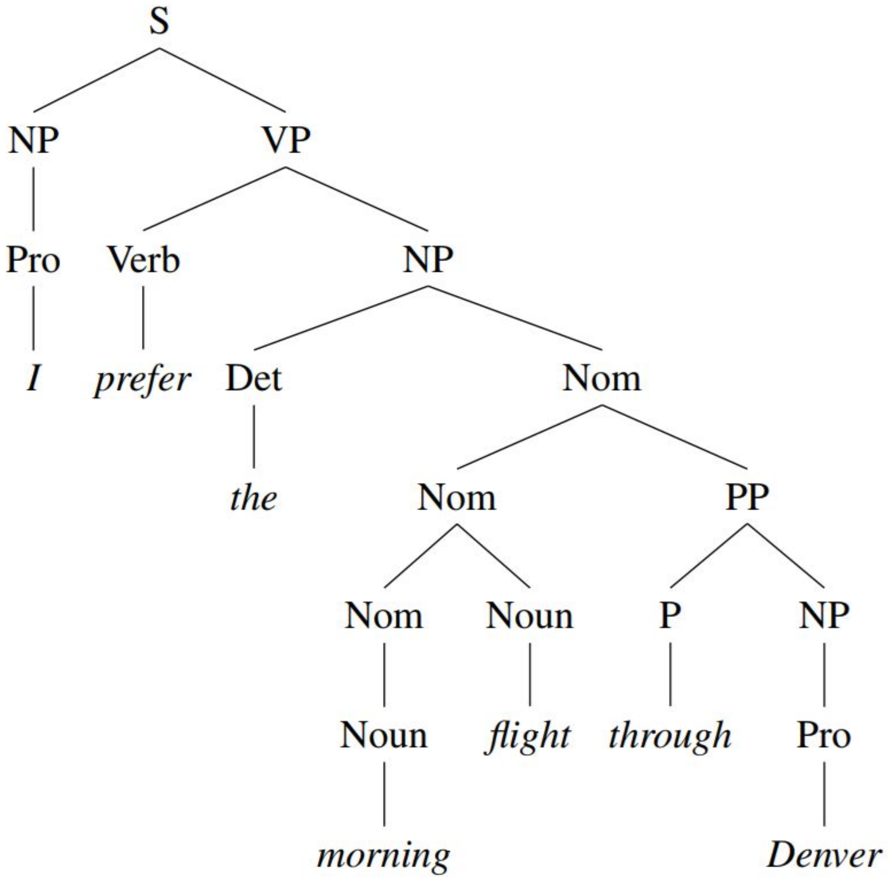
Dependency vs Constituency

- Dependency structures explicitly represent
  - head-dependent relations (directed arcs),
  - functional categories (arc labels)
  - possibly some structural categories (parts of speech)

- Phrase (aka constituent) structures explicitly represent
  - phrases (nonterminal nodes),
  - structural categories (nonterminal labels)

Dependency vs Constituency trees





Parsing Languages with Flexible Word Order

I prefer the morning flight through Denver

Я предпочитаю утренний перелет через Денвер

Languages with free word order

I prefer the morning flight through Denver

Я предпочитаю утренний перелет через Денвер

Я предпочитаю через Денвер утренний перелет

Утренний перелет я предпочитаю через Денвер

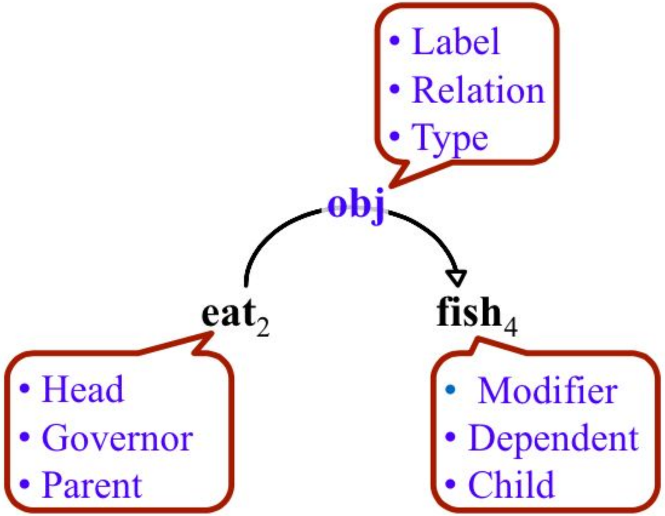
Перелет утренний я предпочитаю через Денвер

Через Денвер я предпочитаю утренний перелет

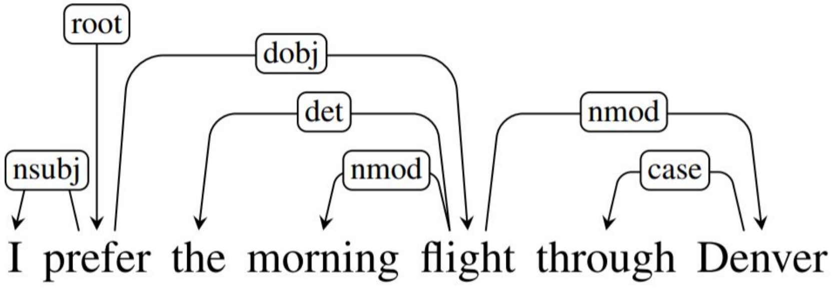
Я через Денвер предпочитаю утренний перелет

...

Dependency relations



Types of relationships



- The clausal relations NSUBJ and DOBJ identify the arguments: the subject and direct object of the predicate *cancel*

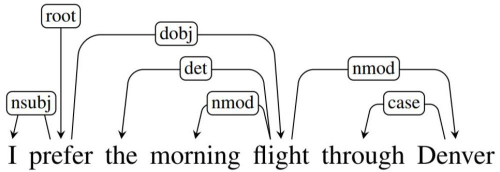
- The NMOD, DET, and CASE relations denote modifiers of the nouns *flights* and *Houston*.

Grammatical functions

Clausal Argument Relations	Description
NSUBJ	Nominal subject
DOBJ	Direct object
IOBJ	Indirect object
CCOMP	Clausal complement
XCOMP	Open clausal complement
Nominal Modifier Relations	**Description**
NMOD	Nominal modifier
AMOD	Adjectival modifier
NUMMOD	Numeric modifier
APPOS	Appositional modifier
DET	Determiner
CASE	Prepositions, postpositions and other case markers
Other Notable Relations	**Description**
CONJ	Conjunct
CC	Coordinating conjunction

Figure 13.2 Selected dependency relations from the Universal Dependency set. (de Marneffe et al., 2014)

Dependency Constraints

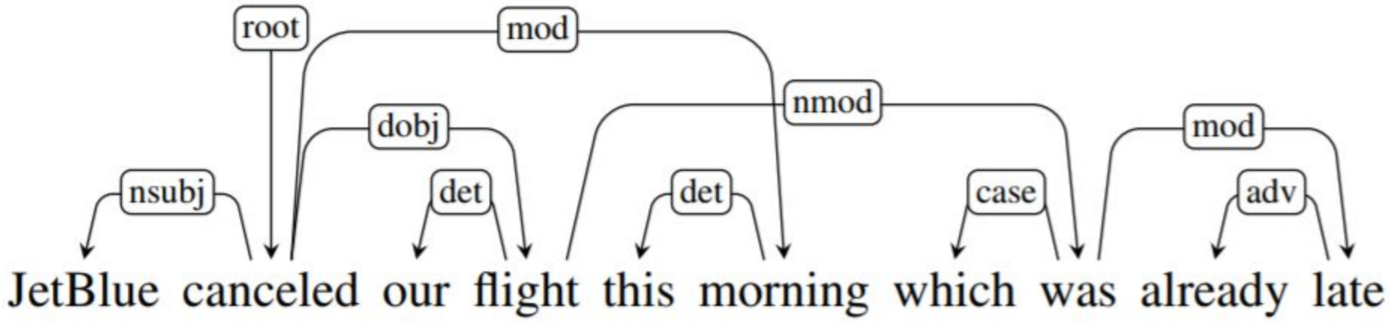


- Syntactic structure is complete (connectedness)
  - connectedness can be enforced by adding a special root node
- Syntactic structure is hierarchical (acyclicity)
  - there is a unique pass from the root to each vertex
- Every word has at most one syntactic head (single-head constraint)
  - except root that does not have incoming arcs

This makes the dependencies a tree

Projectivity

- Projective parse
  - arcs don't cross each other
  - mostly true for English
- Non-projective structures are needed to account for
  - long-distance dependencies
  - flexible word order



Projectivity

- Dependency grammars do not normally assume that all dependency-trees are projective, because some linguistic phenomena can only be achieved using non-projective trees.
- But a lot of parsers assume that the output trees are projective
- Reasons
  - conversion from constituency to dependency
  - the most widely used families of parsing algorithms impose projectivity

Non-Projective Statistics

Arabic: 11.2 %

Bulgarian: 5.4 %

Chinese: 0.0 %

Czech: 23.2 %

Danish: 15.6 %

Dutch: 36.4 %

German: 27.8 %

Japanese: 5.3 %

Polish: 18.9 %

Slovene: 22.2 %

Spanish 1.7 %

Swedish: 9.8 %

Turkish: 11.6 %

English: 0.0% (SD: 0.1%)

Percentage of non-projective trees for some treebanks of the CoNLL-X Shared Task and English.

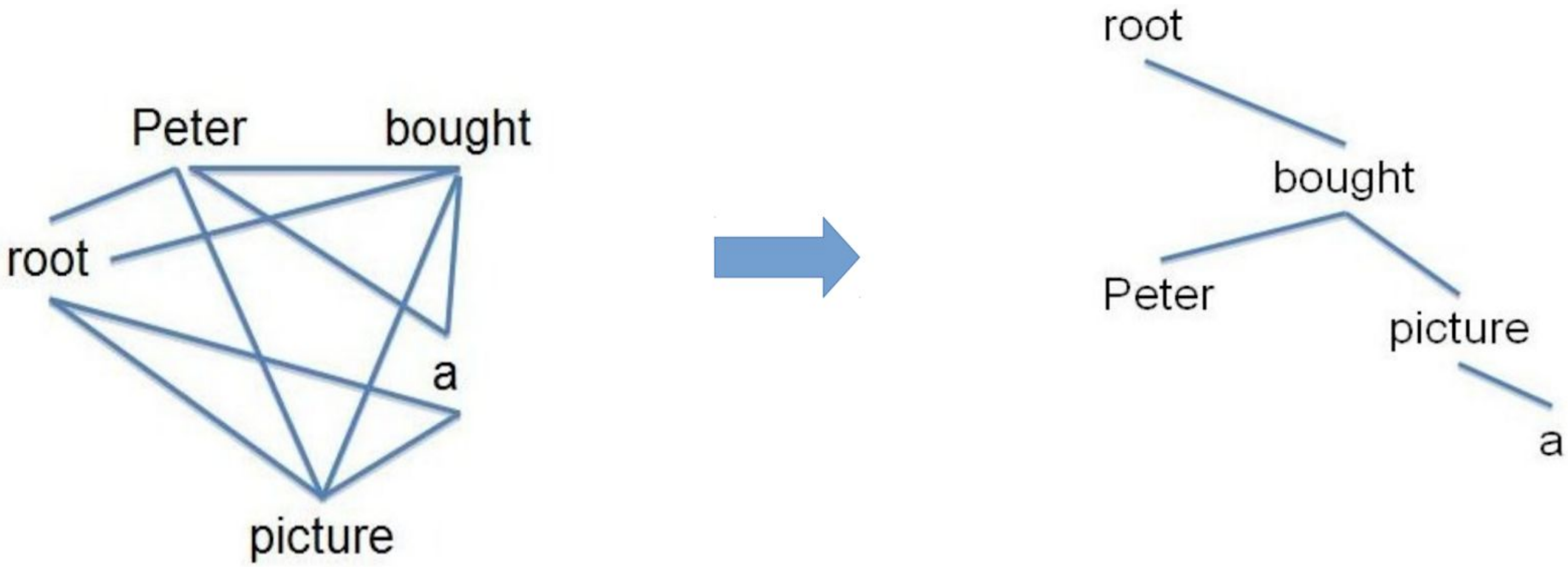
Parsing problem

The parsing problem for a dependency parser is to find the optimal dependency tree ***y*** given an input sentence ***x***

This amounts to assigning a syntactic head ***i*** and a label ***l*** to every node ***j*** corresponding to a word x_j in such a way that the resulting graph is a tree rooted at the node 0

Parsing problem

- This is equivalent to finding a spanning tree in the complete graph containing all possible arcs



Parsing algorithms

- Transition based
  - greedy choice of local transitions guided by a good classifier
  - deterministic
  - MaltParser (Nivre et al. 2008)
- Graph based
  - Minimum Spanning Tree for a sentence
  - McDonald et al.'s (2005) MSTParser
  - Martins et al.'s (2009) Turbo Parser