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Plan

- 1. What is parsing and why we need it
- 2. Phrase structure grammar
 - a. Intuition
 - b. Formal grammars
 - c. CKY-algorithms
 - d. *Shallow parsing
 - e. Probabilistic grammars
 - f. Probabilistic grammars lexicalization
 - g. Quality evaluation
 - h. Tools and data

Parsing

machine analysis of the text structure, esp. the sentence structure

We've all done it at school, and sometimes machines can do it as well



Motivation

Sentence structure itself is never a goal for practical tasks, but is extremely useful as a preprocessing step e.g. for:

- facts extraction and opinion mining,
- text summarization,
- machine translation, etc.

https://static-eu.insales.ru/images/products/1/850/61170514/9031 P open 1 wo c 1800x http://papus666.narod.ru/clipart/g/gaek/gaechnkl017.png https://www.microscope.com/media/catalog/product/cache/2/image/9df78eab335252008d6e

Syntax

grammar subset studying sentences and ways of combining words within a sentence

Main approaches to syntax description

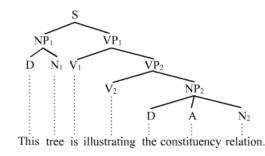
- 1) dependency grammar Tesnière, L. 1959. Éléments de syntaxe structurale. Paris: Klincksieck
- 2) phrase structure grammars

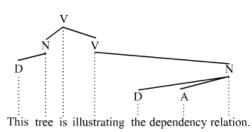
Chomsky, Noam 1957. Syntactic structures. The Hague/Paris: Mouton

3) link grammar

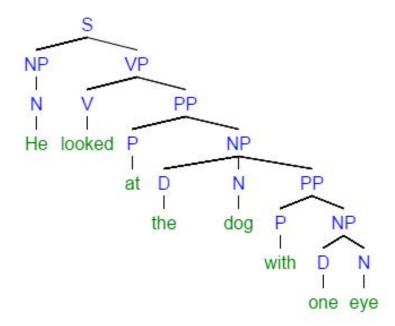
Daniel Sleator and Davy Temperley. 1991. Parsing English with a Link Grammar. Carnegie Mellon University Computer Science technical report, October 1991.

4) hybrid approaches



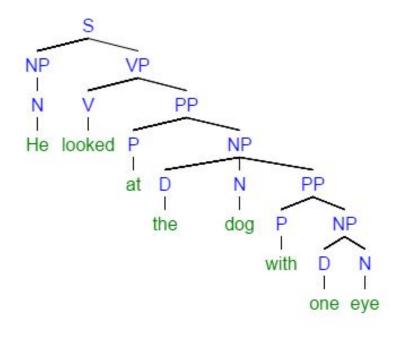


Before we define stuff thoroughly: an example



Is everything OK here?

Before we define stuff thoroughly: an example



Is everything OK here?

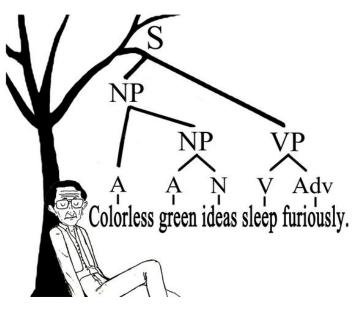
Yes! But if we want to say one has LOOKED with one eye, then the tree should be different

This is called **attachment ambiguity** ("dunno where to hang the subtree")

coordination ambiguity
is widely spread as well:
[old [men and women]] vs [old men] and [women]

Example, discussion

- There may be several parse trees, this is OK (BTW, there are parsers that yield multiple parse trees given the text)
- sometimes there is only one 'true' parse tree, and this is evident for us, but not for the machine, because we know word meanings, context and how this world works in general
- it is also hard thanks to:
 - ellipsis (omission of the word),
 - context-dependent meanings ("watch TV", "how come they got into TV"),
 - morphological ambiguity ("river flow", "the river can flow")



http://www.jnanam.net/slade/Trees/colourless_green_ideas.jpg?w=240

Where the rules come from

- Experts (weak, expensive)
- Annotated data (great, also expensive)

Data banks, where the sentences are parsed

Интересно	A KP EA CPEA]
что предик +	
<i>B</i>	(1-компл) > В [PR]
этой	опред > ЭТОТ (А ЕД ЖЕН ПР)
акции	предл 🔶 АКЦИЯ [S ЕД ЖЕН ПР НЕОД]
вместе	MODET → BMECTE [ADV]
c	(1-компл) + C [PR]
Матвеем	предл 🗨 МАТВЕЙ [S ЕД МУЖ ТВОР ОД]
Платовым	аппоз > ПЛАТОВ [S ЕД МУЖ ТВОР ОД]
участвовал	(подч-союзн) • УЧАСТВОВАТЬ (V НЕСОВ ИЗЪЯВ ПРОШ ЕД МУЖ)
<i>u</i>	огранич >> И [PART]
020	1-компл → ● ОН [S ЕД МУЖ РОД ОД]
отец	предик > (ОТЕЦ [S ЕД МУЖ ИМ ОД]
Иван	аппоз > NBAH [S ЕД МУЖ ИМ ОД]
Федорович	аппоз → ФЕДОРОВИЧ [S ЕД МУЖ ИМ ОД]

```
( (S (NP-SBJ-1 Jones)
     (VP followed
         (NP him)
          (PP-DIR into
                  (NP the front room))
          (S-ADV (NP-SBJ *-1)
                 (VP closing
                     (NP the door)
                     (PP behind
                          (NP him)))))
     .))
( (S (ADVP-LOC Here)
     (NP-SBJ-1 he)
     (VP could
         n't
         (VP be
              (VP seen
                  (NP *-1)
                  (PP by
                      (NP-LGS (NP Blue Throat)
                               and
                               (NP his gang))))))
     .))
```

Plan

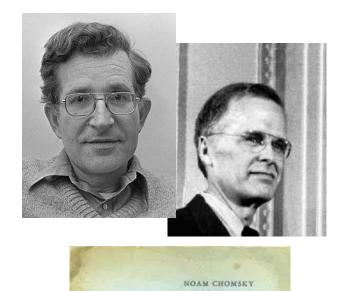
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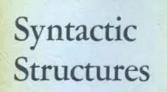
Phrase structure grammar

Key points

- some words are 'connected more tightly with each other' than other ones
- the words in a sentence can be grouped into phrases, that 'behave like a single language entity'
- phrases can be nested

First formulated by Wilhelm Wundt (1900), formalized by **Noam Chomsky** (1956) and by **John Backus** (1959; BNF; independently).





Illustration

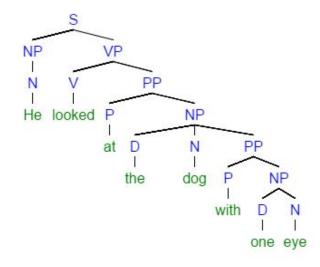
Phrases can be swapped

On September seventeenth, I'd like to fly from Atlanta to Denver I'd like to fly *on September seventeenth* from Atlanta to Denver I'd like to fly from Atlanta to Denver *on September seventeenth*

yet words forming a phrase sometimes can't

*On September, I'd like to fly <u>seventeenth</u> from Atlanta to Denver *<u>On</u> I'd like to fly September seventeenth from Atlanta to Denver *I'd like to fly on September from Atlanta to Denver <u>seventeenth</u>

Parse tree example



VP - verb phrase (approx: a verb and dependent PoS)

NP - noun phrase (approx: a noun is a root)

PP - prepositional phrase**AP** - adjective phrase

https://i.imgur.com/ShMtNEy.png

D (**Det**) - determinatives: articles, certain pronouns, quantifiers, numbers, Q-words, etc.

Formal grammar rules

Formal grammar can be treated as a set of rules, which, after a sequence of applications to the initial symbol (**S**), we use to 'generate' the text

Parse tree in the example could be built ONLY if the grammar contains this set of rules:

 $\textbf{S} \rightarrow \textbf{NP} \ \textbf{VP}$

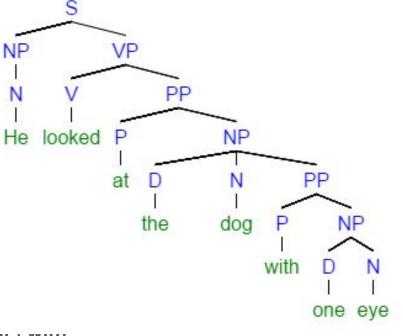
 $NP \rightarrow N$

 $NP \rightarrow D N$

- $NP \rightarrow D N PP$
- $VP \rightarrow V PP$

 $\mathbf{PP} \to \mathbf{P} \; \mathbf{NP}$

 $N \rightarrow He \mid dog \mid eye, V \rightarrow looked, D \rightarrow the \mid one, P \rightarrow ac \mid with the look of the$



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Definition

Formal grammar (aka context-free grammar) is a tuple of...

- N a set of nonterminal symbols (e.g., NP, VP, N,...)
- Σ a set of terminal symbols (all symbols but ones in N)
- R a set of production rules of type: $\textbf{A} \rightarrow \textbf{\beta}$,

where

A — a nonterminal symbol,

 β — a string, an element of the set of all possible strings over Σ and N: ($\Sigma \cup N$)*

S — a special 'starting' symbol in **N**

Then **the language defined by this grammar** is a set of all strings over Σ , that can be deduced from **S** using the production rules: L = {w | w is in Σ * and S \Rightarrow w}

Chomsky Normal Form (CNF)

Any context-free grammar can be converted to the equivalent one (in terms of the defined language) that would contain production rules that would 'generate' not more than 2 'branches', e.g.:



How to parse any CFG

Naive approach: traverse all possible parse trees? :)

Grammars are well studied objects, those who have taken classes on compilers should be very familiar with ones

Program code is long; one needs very effective algorithms to parse it

Sentences in natural languages are usually shorter (though some extremes exist), hence the requirements to parsing speed are lower. We will take a look at probably the simplest algorithm

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Cocke-Younger-Kasami algorithm (CYK)

From bottom to top, dynamic programming, the grammar should be in the form of CNG

The idea, first approximation: for the sentence of length N, fill the 3D array with markers **p[l, s, a]** determining whether *there is a rule that parses the substring* **a[s:s+l]**

$S \longrightarrow NP VP$	CYK table						
$VP \rightarrow VP PP$	S						
$VP \rightarrow VNP$			ĺ				
$V\!P ~ ightarrow eats$	-	VP		1			
$PP ightarrow \ P \ NP$							
$NP \hspace{.1in} ightarrow \hspace{.1in} Det \hspace{.1in} N$	S				Ĩ		
NP ~ ightarrow she			(6			
V o eats		VP			PP		-
P o with	S		NP			NP	
$N ~~ ightarrow~{\it fish}$	NP	V, VP	Det.	N	Р	Det	N
N ~ ightarrow fork	she			field			fork
Det ~ ightarrow ~a	she	eats	а	fish	with	а	fork

let the input be a string *I* consisting of *n* characters: $a_1 \ldots a_n$. **let** the grammar contain *r* nonterminal symbols $R_1 \ldots R_r$, with start symbol R_1 . **let** P[n,n,r] be an array of booleans. Initialize all elements of *P* to false.

The input is a sentence of length **n** Boolean 3D array **P** is initialized with **False**

let the input be a string I consisting of n characters: $a_1 \ldots a_n$. let the grammar contain r nonterminal symbols $R_1 \ldots R_r$, with start symbol R_1 . let P[n,n,r] be an array of booleans. Initialize all elements of P to false.

```
for each s = 1 to n
for each unit production R<sub>v</sub> -> a<sub>s</sub>
set P[1,s,v] = true
```

First we traverse the rules of the kind $\mathbf{A} \rightarrow \mathbf{\beta}$, where $\mathbf{\beta}$ is a terminal symbol, and set for those $\mathbf{\beta}$ s TRUE for the corresponding rules and length = 1

let the input be a string I consisting of n characters: $a_1 \ldots a_n$. let the grammar contain r nonterminal symbols $R_1 \ldots R_r$, with start symbol R_1 . let P[n,n,r] be an array of booleans. Initialize all elements of P to false.

```
for each s = 1 to n
for each unit production R<sub>v</sub> -> a<sub>s</sub>
set P[1,s,v] = true
for each l = 2 to n -- Length of span
for each s = 1 to n-l+1 -- Start of span
```

For all substrings set by length I and starting index s

let the input be a string I consisting of n characters: $a_1 \ldots a_n$. let the grammar contain r nonterminal symbols $R_1 \ldots R_r$, with start symbol R_1 . let P[n,n,r] be an array of booleans. Initialize all elements of P to false.

```
for each s = 1 to n

for each unit production R_v \rightarrow a_s

set P[1,s,v] = true

for each l = 2 to n \rightarrow Length of span

for each s = 1 to n - l + 1 \rightarrow Start of span

for each p = 1 to l - 1 \rightarrow Partition of span

for each production R_a \rightarrow R_b R_c

if P[p,s,b] and P[l-p,s+p,c] then set P[l,s,a] = true

R_b \rightarrow w R_c \rightarrow w
```

...and all possible splits into two substrings we check if there is such a way to parse each of the two substrings so that their 'heads' (here: R_b and R_c) are in the right side of some rule (here: $R_a \rightarrow R_b R_c$)

If yes, set the corresponding array element to **True**.

let the input be a string I consisting of n characters: $a_1 \ldots a_n$. let the grammar contain r nonterminal symbols $R_1 \ldots R_r$, with start symbol R_1 . let P[n,n,r] be an array of booleans. Initialize all elements of P to false.

```
for each s = 1 to n
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    set P[1,s,v] = true
for each l = 2 to n - Length of span
  for each s = 1 to n-l+1 -- Start of span
    for each p = 1 to l-1 -- Partition of span
      for each production R_a \rightarrow R_b R_c
        if P[p,s,b] and P[l-p,s+p,c] then set P[l,s,a] = true
if P[n,1,1] is true then
  I is member of language
else
  I is not member of language
```

CYK-algorithm: discussion

- As in Viterbi algorithms, we can store backpointers and do a backward pass to recover **all possible parse trees**
- There may exist several solutions, usually we need just one
- For the analysis we have to 'denormalize' CFG back from CNF
- Cubic complexity: **O**(**n**³ |**G**|)
- Complexity for parsing with arbitrary CFGs can be reduced in terms of the 'big O', e.g. using the fast matrix product Valiant, Leslie G. (1975). "General context-free recognition in less than cubic time". J. Comput. Syst. Sci. 10 (2): 308–314.

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BTW: shallow parsing

Sometimes for practical tasks shallow parsing is enough, e.g. **chunking** extracting several non-intersecting phrases

[$_{NP}$ The morning flight] [$_{PP}$ from] [$_{NP}$ Denver] [$_{VP}$ has arrived.]

E.g. we want to extract noun phrases:

[$_{NP}$ The morning flight] from [$_{NP}$ Denver] has arrived.

This can even be treated as a sequence learning task

The morning flight from Denver has arrived.B_NP I_NPI_NP OB_NP OO

To evaluate all this, we compute precision, recall and f-measure for the selected chunks, taking exact borders matches + tags matches

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Probabilistic Context-Free Grammars (PGFG)

...are a way to choose the best possible parse; we'll assign probability to each production rule

- **N** a set of nonterminal symbols (e.g., *NP*, *VP*, *N*,...)
- Σ a set of terminal symbols (all symbols but ones in **N**)
- **R** a set of production rules of type: $\mathbf{A} \rightarrow \boldsymbol{\beta}$ [p],

where

A — a nonterminal symbol,

 β — a string, an element of the set of all possible strings over Σ and N: (Σ U N)*

 $p(\beta|A)$ — a number between 0 and 1, such that $\Sigma_{\beta} p(\beta|A) = 1$

 \mathbf{S} — a special 'starting' symbol in \mathbf{N}

PCFG is consistent if the sum of probabilities of all possible sentences in the language in concern =1

PCFG in action

The probability of the parse tree T for the sentence S is a product of all production rules that 'were applied during the generation of the sentence'

$$P(T,S) = \prod_{i=1}^{n} P(RHS_i | LHS_i)$$

also we know that

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

and **P(S|T) = 1**, because the parse contains all sentence's words **S**, so

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

PCFG in action

This is what it looks like —

Having multiplied conditional probabilities we get probabilities of parse trees P(T) and choose the most probable one

But what we need is

 $\hat{T}(S) = \underset{Ts.t.S=\text{yield}(T)}{\operatorname{argmax}} P(T|S)$

However, if we use Bayes rule and the fact that P(S,T) = P(T) it is easy to show this is correct

	R	ules	Р
S	\rightarrow	VP	.05
VP	\rightarrow	Verb NP	.20
NP	\rightarrow	Det Nominal	.20
Nominal	\rightarrow	Nominal Noun	.20
Nominal	\rightarrow	Noun	.75

Verb	\rightarrow	book	.30
Det	\rightarrow	the	.60
Noun	\rightarrow	dinner	.10
Noun	\rightarrow	flight	.40

Training: CYK again

Exactly the same algorithm, but

- boolean-valued array P => probabilities
- setting **True** for any good split =>
 updating the probability if it's greater than the current value

if $(table[i,j,A] < P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C])$ **then** $table[i,j,A] \leftarrow P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]$

CYK: before

```
let the input be a string I consisting of n characters: a_1 \ldots a_n.
let the grammar contain r nonterminal symbols R_1 \ldots R_r, with start symbol R_1.
let P[n,n,r] be an array of booleans. Initialize all elements of P to false.
for each s = 1 to n
  for each unit production R_v \rightarrow a_s
    set P[1,s,v] = true
for each l = 2 to n -- Length of span
  for each s = 1 to n-l+1 -- Start of span
    for each p = 1 to l-1 -- Partition of span
      for each production R_a \rightarrow R_b R_c
        if P[p,s,b] and P[l-p,s+p,c] then set P[l,s,a] = true
if P[n,1,1] is true then
  I is member of language
else
  I is not member of language
```

CYK: after

```
let the input be a string I consisting of n characters: a_1 \ldots a_n.
let the grammar contain r nonterminal symbols R_1 \ldots R_r, with start symbol R_1.
let P[n,n,r] be an array of real numbers. Initialize all elements of P to zero.
let back[n,n,r] be an array of backpointing triples.
for each s = 1 to n
                                                       the probability of the production rule
  for each unit production R_v \rightarrow a_s
    set P[1,s,v] = Pr(R_v \rightarrow a_s)
                                                       MAX probability of the parse I[s:s+p]
for each l = 2 to n -- Length of span
                                                        MAX probability of the parse I[s+p:s+l]
  for each s = 1 to n-l+1 -- Start of span
    for each p = 1 to l-1 -- Partition of span
      for each production R_a \rightarrow R_b R_c
        prob splitting = Pr(R_a \rightarrow R_b R_c) * P[p,s,b] * P[l-p,s+p,c]
        if P[p,s,b] > 0 and P[l-p,s+p,c] > 0 and P[l,s,a] < prob splitting then
           set P[l,s,a] = prob splitting
           set back[l,s,a] = <p,b,c>
```

Where do we get probabilities from?

Where do we get probabilities from?

Obtain a treebank and compute production rules applications frequencies

$$P(\alpha \to \beta | \alpha) = \frac{\operatorname{Count}(\alpha \to \beta)}{\sum_{\gamma} \operatorname{Count}(\alpha \to \gamma)} = \frac{\operatorname{Count}(\alpha \to \beta)}{\operatorname{Count}(\alpha)}$$

Also the approaches incrementally updating rules probabilities exist

PCFG: discussion

- + Usable way to train grammar parsers using a corpus
- + Works better than previous approaches
- + The effective parsing algorithms exist
- Independence assumptions are too strong (still many errors)
- Weak expressiveness:
 - it is useful to take 'connections types' into account: subject/object
 - many rules and regularities are connected with certain words

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Head of a phrase

It is important to be able to determine which element (non-terminal symbol) of the phrase is the main one

It is a discussed and a non-trivial task, despite it may not seem to be so. In English it is well-solved by the **rules** of the sort:

- If the last word is tagged POS, return last-word.
- Else search from right to left for the first child which is an NN, NNP, NNPS, NX, POS, or JJR.
- Else search from left to right for the first child which is an NP.
- Else search from right to left for the first child which is a \$, ADJP, or PRN.
- Else search from right to left for the first child which is a CD.
- Else search from right to left for the first child which is a JJ, JJS, RB or QP.
- · Else return the last word

Why did we talk about that? Lexicalization!

Phrase head elements can serve as a helpful context!

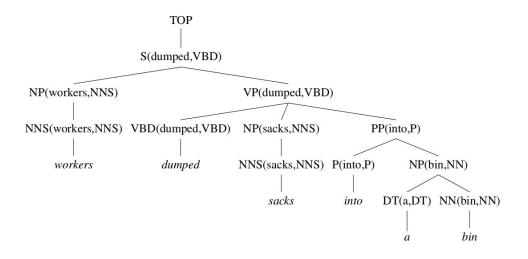
We can set it by appending carefully chosen terminal symbols (and head non-terminal symbols) to non-terminal ones

Probabilistic Lexicalized CFGs Charniak's and Collins' parsers

Charniak, E. (1997). Statistical parsing with a context-free grammar and word statistics. In AAAI-97, pp. 598–603. AAAI Press.

Collins, M. (1999). Head-Driven Statistical Models for Natural Language Parsing. Ph.D. thesis, University of Pennsylvania, Philadelphia.

For more details — Martin, Jurafsky, Collins books and materials



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Quality evaluation

Suppose we have the gold standard for parse trees, let us look at the **exact match of phrases borders and labels**:

labeled recall: = $\frac{\text{# of correct constituents in hypothesis parse of s}}{\text{# of correct constituents in reference parse of s}}$

labeled precision: = $\frac{\text{\# of correct constituents in hypothesis parse of }s}{\text{\# of total constituents in hypothesis parse of }s}$

...that is, as usual, fraction of correctly predicted items among true ones / all predicted respectively

cross-brackets: cases of the kind ((A B) C) in a "gold standard" (A (B C)) in prediction

If labels themselves are not important, one can use other evaluation methods

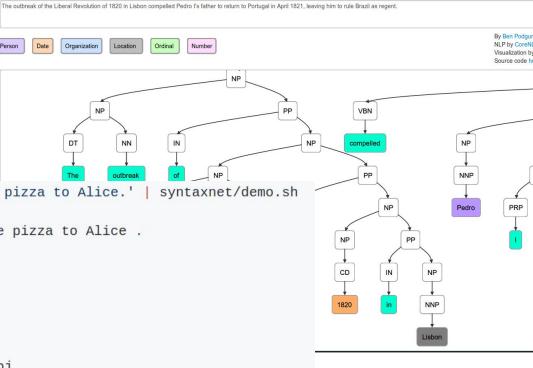
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Instruments

- nltk
- pattern
- spaCy, CoreNLP, CleanNLP (are said to be fast)
- MATE
- SyntaxNet

DT NN IN outbreak echo 'Bob brought the pizza to Alice.' Input: Bob brought the pizza to Alice . Parse: brought VBD ROOT +-- Bob NNP nsubj +-- pizza NN dobj +-- the DT det +-- to IN prep +-- Alice NNP pobj +-- . . punct





Syntax formalism

https://en.wikipedia.org/wiki/Treebank#Syntactic_treebanks

Duich		Dependency	License iee
English	Penn Treebank	Phrase structure	Linguistic Data Consortium
English	CCGbank <i>∉</i>	Combinatory categorial grammar	Linguistic Data Consortium
English	Prague English Dependency Treebank	Dependency	Linguistic Data Consortium
English	Universal Dependencies@	Dependency	Open source (Creative Commons license or GNU general public license)
English	BLLIP WSJ corpus@	Phrase structure	Linguistic Data Consortium
English	British Component of the International Corpus of English (ICE-GB)@	Phrase structure	License fee@
English	Diachronic Corpus of Present-Day Spoken English (DCPSE)	Phrase structure	License fee@
English	Lancaster Parsed Corpus@	Phrase structure	?
English	Susanne Corpus@	Phrase structure	Freely available for research
English	Christine Corpus@	Phrase structure	Freely available for research
English	Lucy Corpus@	Phrase structure	Freely available for research
English	Tübingen Treebank of English / Spontaneous Speech (TüBa-E/S)@	HPSG	Freely available for research
English	LinGO Redwoods@	HPSG	?
English	Multi-Treebank a	Phrase structure	Available online for comparison purposes

Used and recommended materials

- 1. Martin-Jurafsky, Chapters 11-13
- 2. Introduction to Automata Theory, Languages, and Computation John E. Hopcroft, Rajeev Motwani, Jeffrey D. Ullman
- 3. Jarkko Kari, Automata and formal languages, notes
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