Introduction to Natural Language Engineering / Part 11: Parsing & Logical Representation

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Universität Regensburg

Einführung in die Informationslinguistik I / Teil 11: Syntaxanalyse & Einfache Satzsemantik

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Module Overview

- Motivation
- Regular expressions
- Basic statistical natural language processing
- Part-of-speech tagging
- Context-free grammars
- Parsing principles
- Complexity
- Semantics
- Applications: IE, IR, QA, ...

Module Overview (more specific)

- Motivation
- Regular expressions
- Basic statistical natural language processing
- Part-of-speech tagging
- Text classification
- Lexical semantics (embeddings)
- Context-free grammars
- Parsing principles + Complexity
- Applications: IE, IR, QA, ...



Following on from last time ...

- Formal grammars can be used to describe a language
- How do we find out whether a sentence is part of that language?
- That's what a parser will do ...



Parsing

Parsing: Overview



- Parser takes a grammar and an input string and returns possible analyses of that string
- Parsing is a search problem
- Three criteria for evaluating parsers:
 - Correctness
 - Completeness
 - ▶ Efficiency
- Parsing strategies:
 - ▶ Top-down vs. Bottom-Up
 - Breadth-first vs. Depth-first

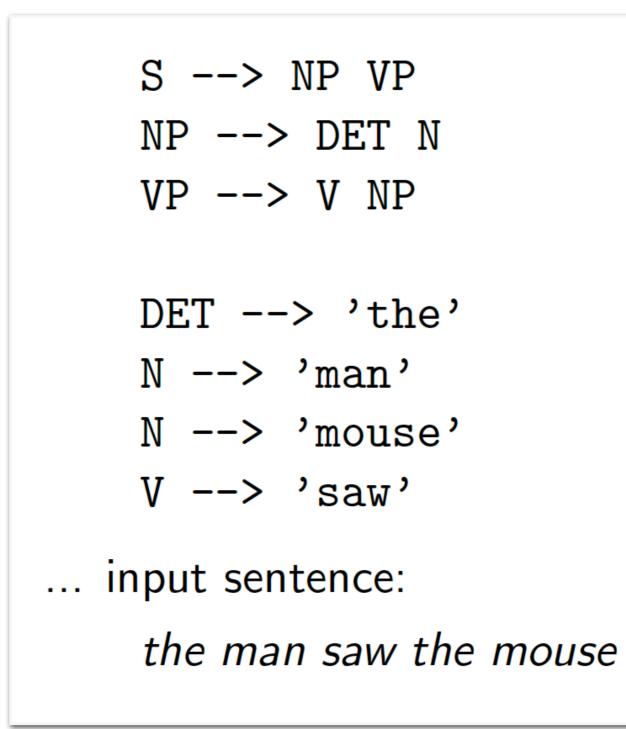


Top-Down Parsing - Strategy

- Start from S (*goal-driven*)
- Look for rules that have S as left-hand side and replace S by the right-hand side of the rule
- Progressively refine structures by performing this for the resulting string replacing *non-terminals* by right-hand sides of rules
- Finished when the result finally matches the input sentence



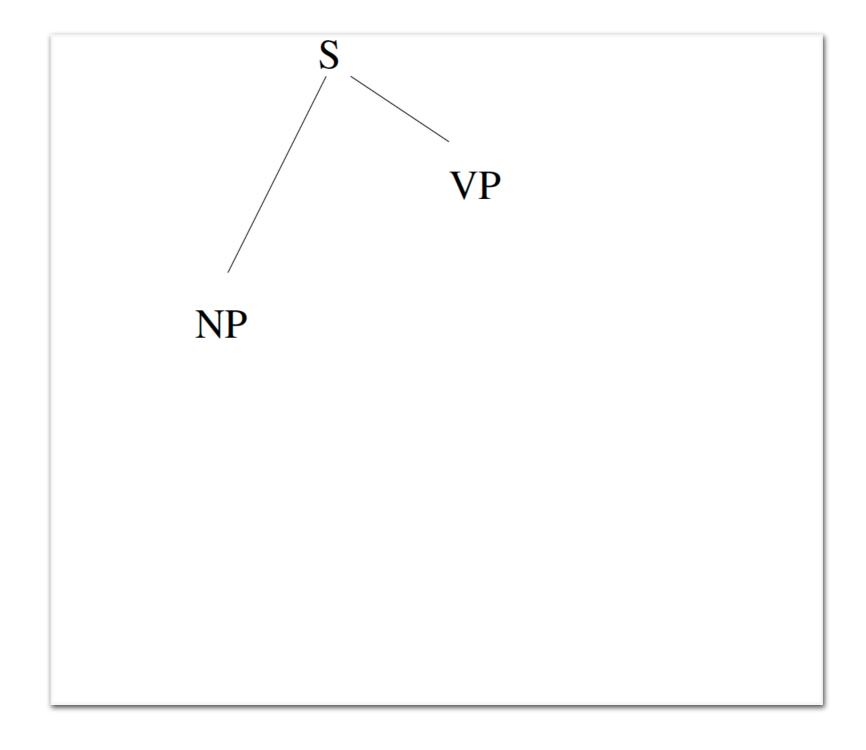
Top-Down Parsing -Example Grammar



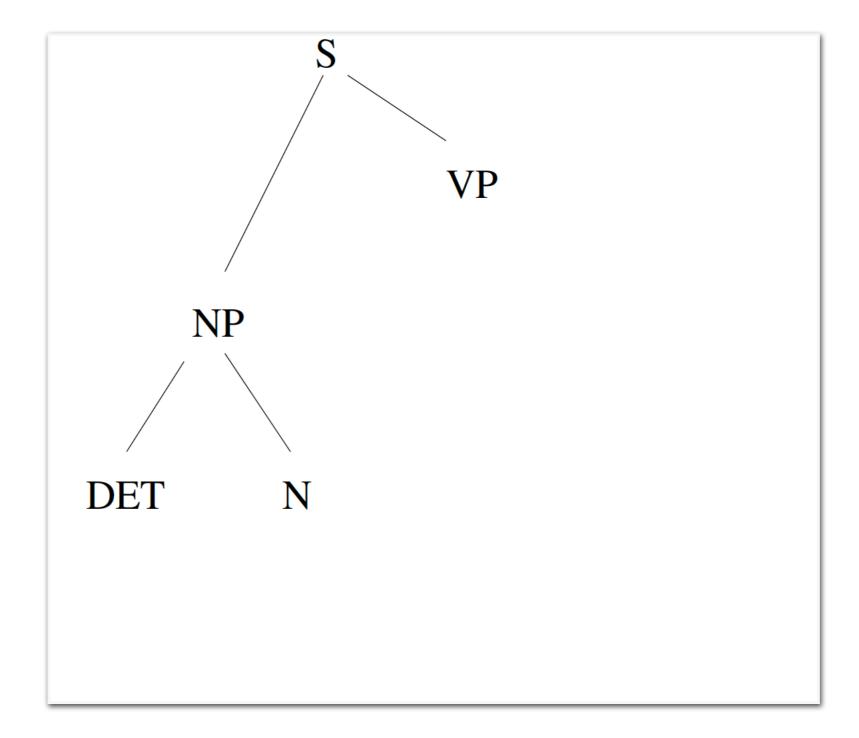




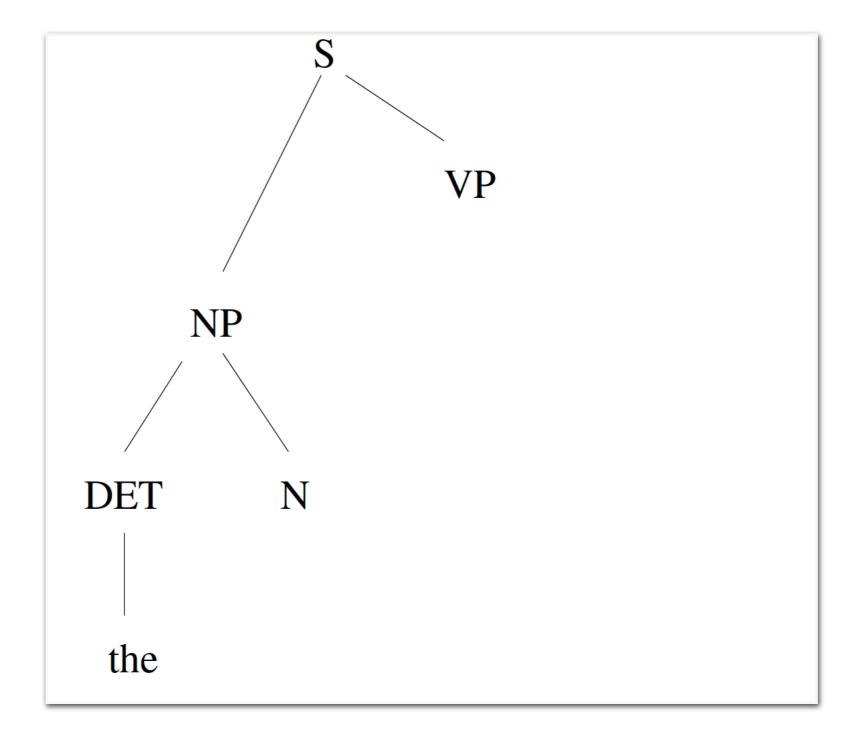
Top-Down Parsing - Example



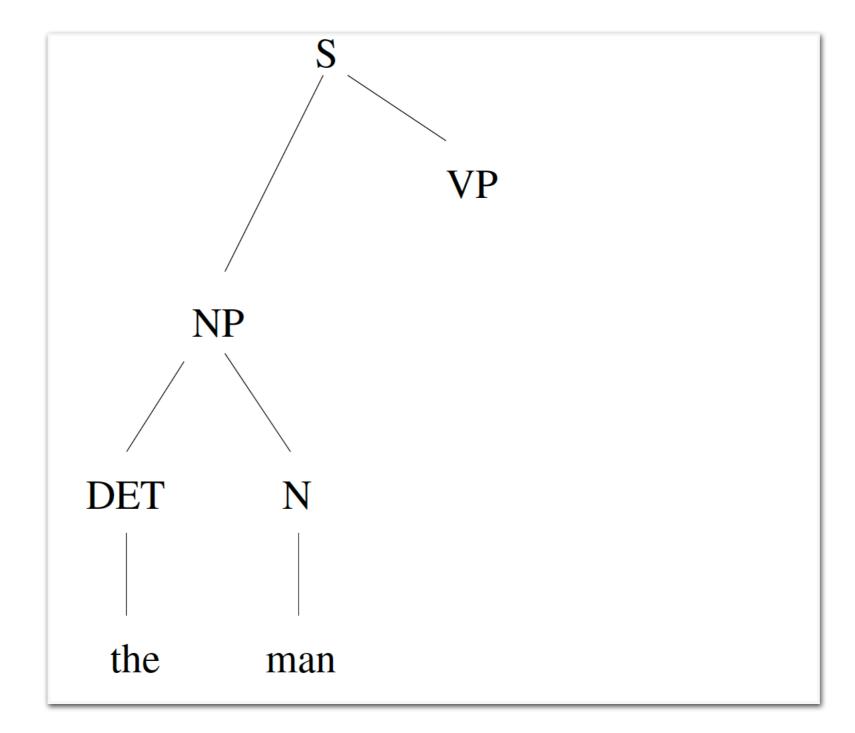




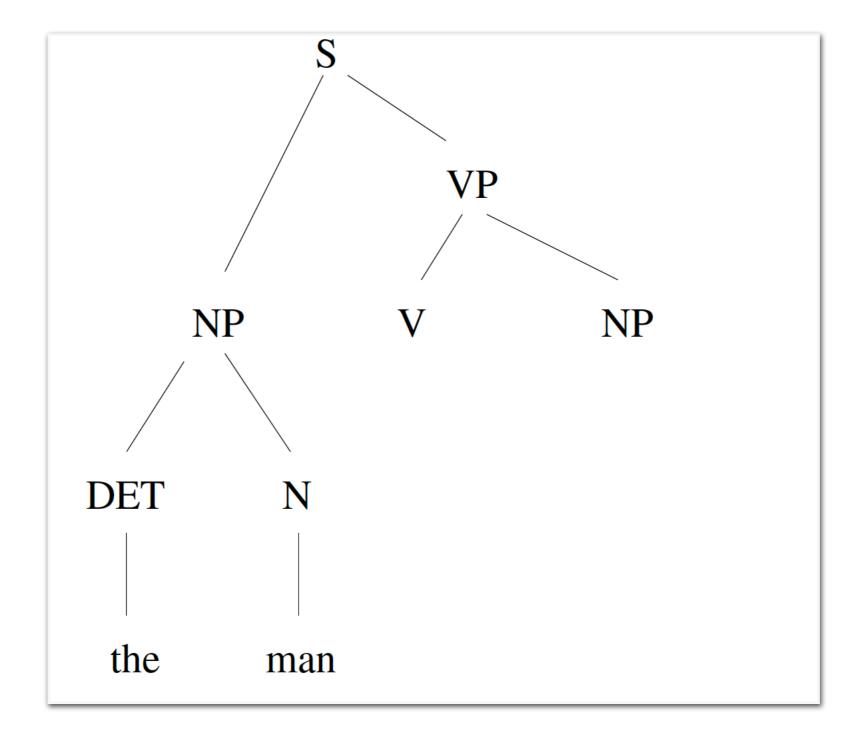




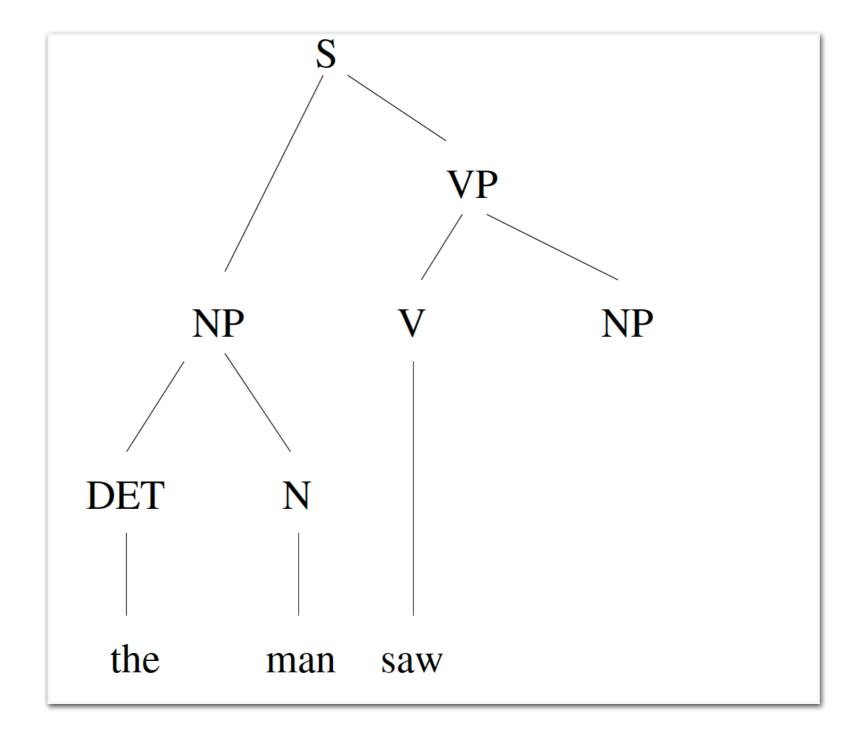




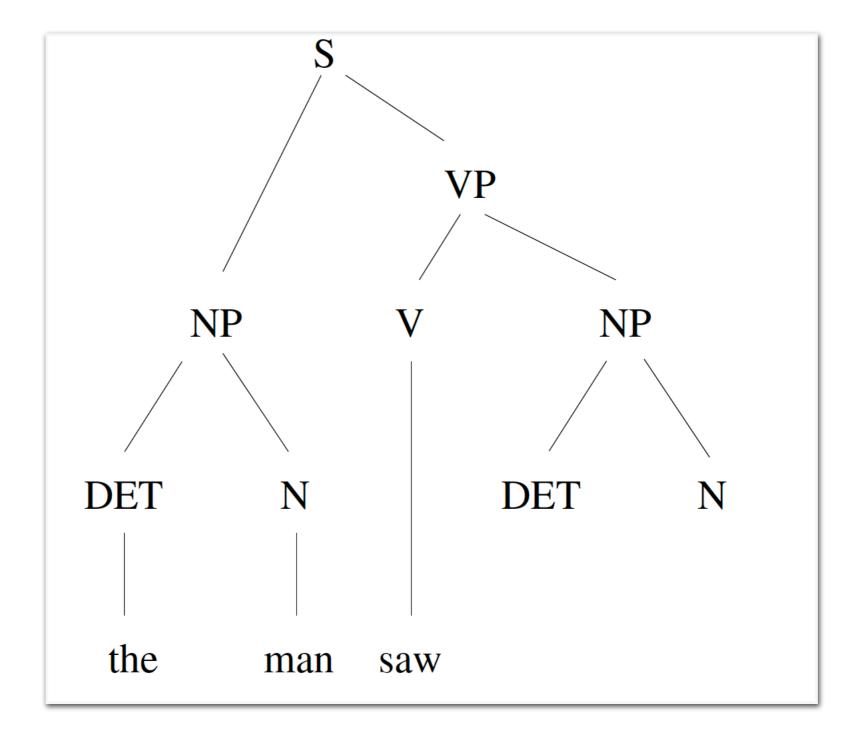




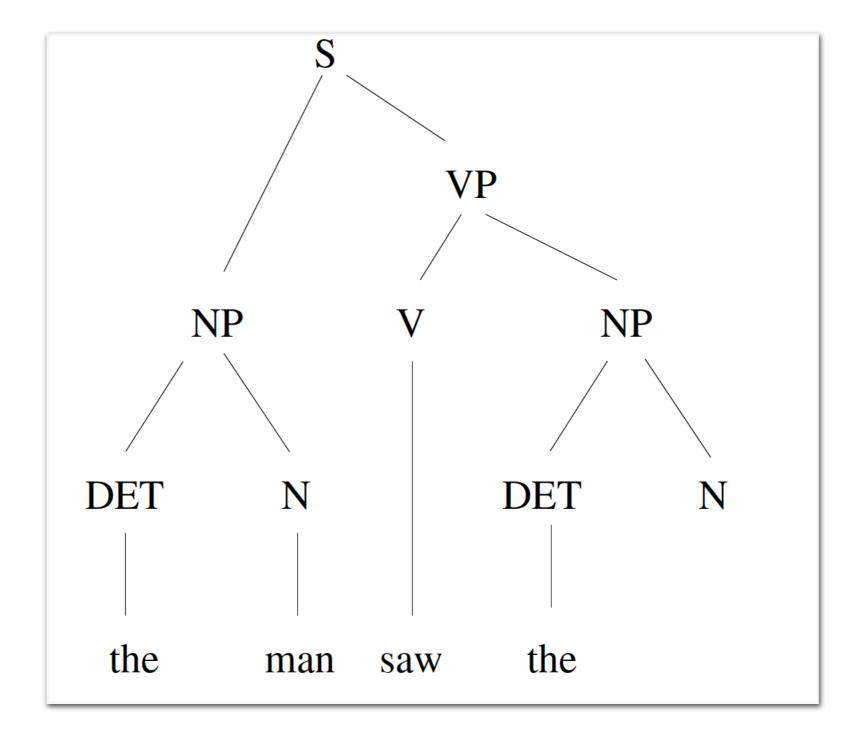




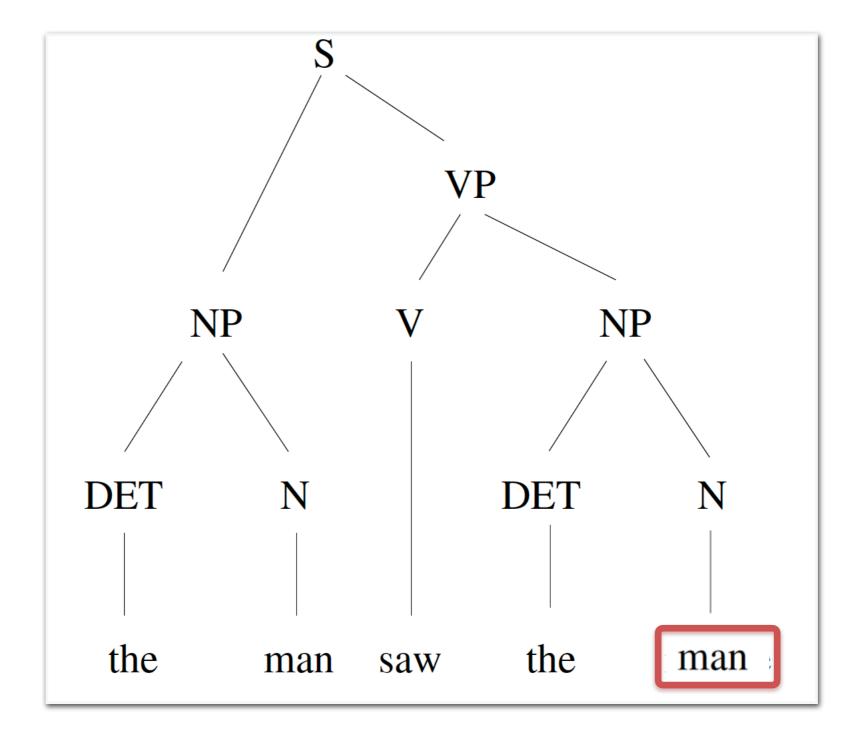




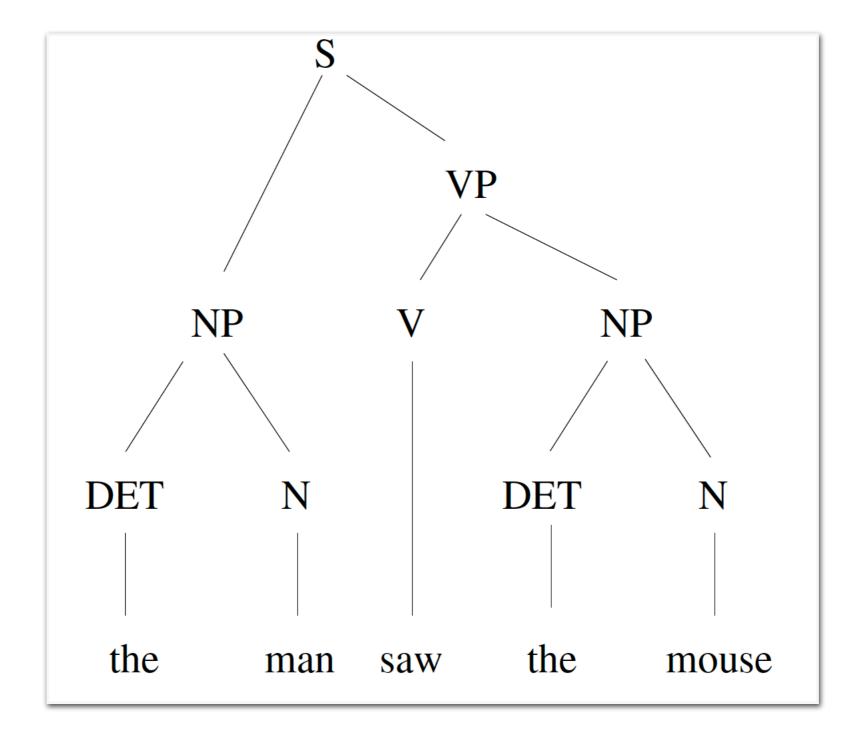














Top-Down Parsing - Problems

- Left recursion
- Structural ambiguity

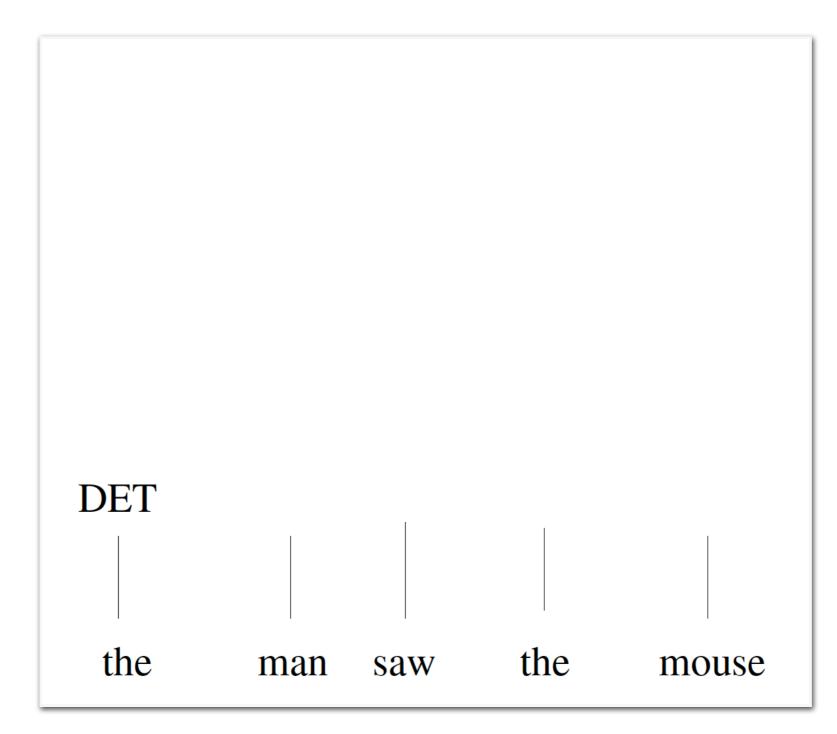


Bottom-Up Parsing - Strategy

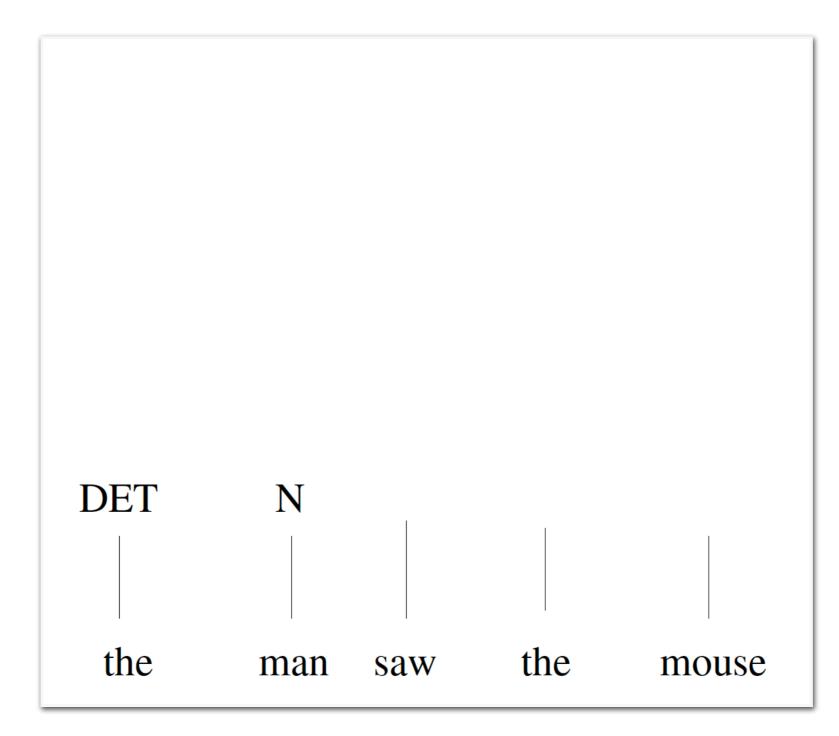
- Start from word level (*data-driven*)
- Progressively building up structures
- Find strings in the input that are right-hand sides of rules and can be replaced by the corresponding left-hand side
- Finished when the result is S



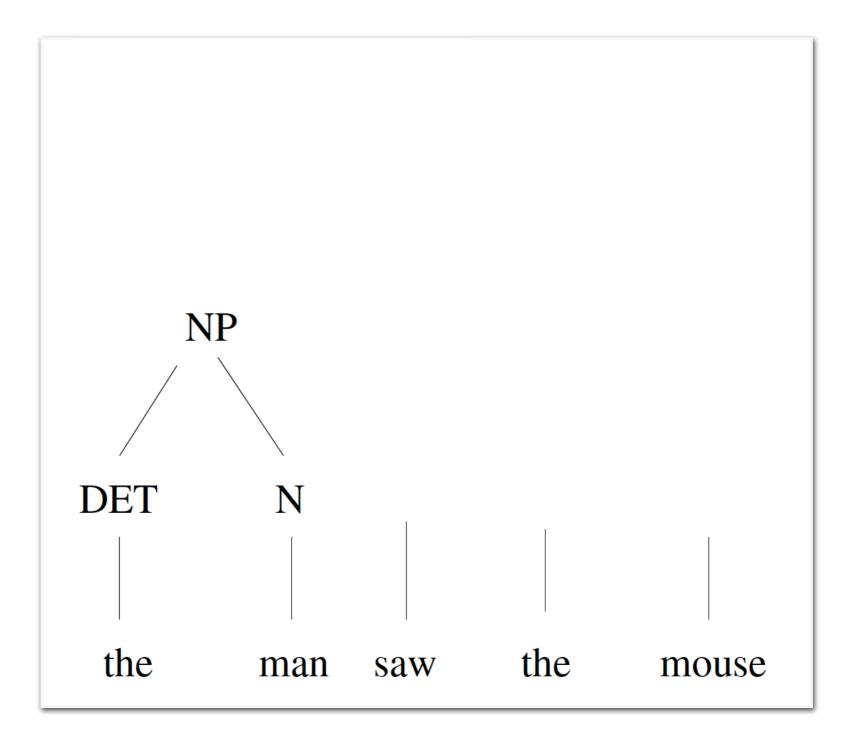




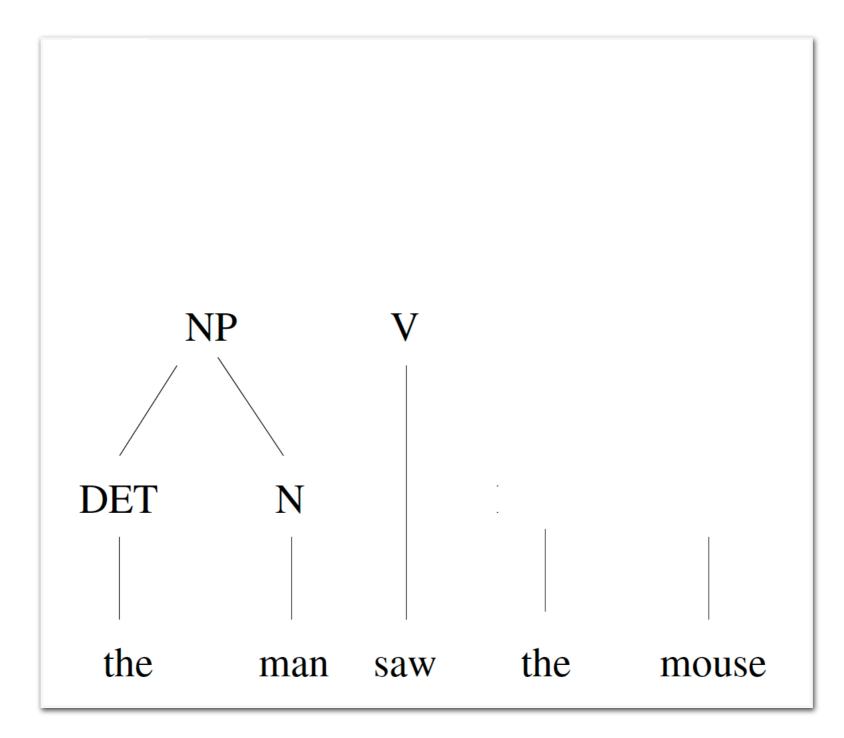




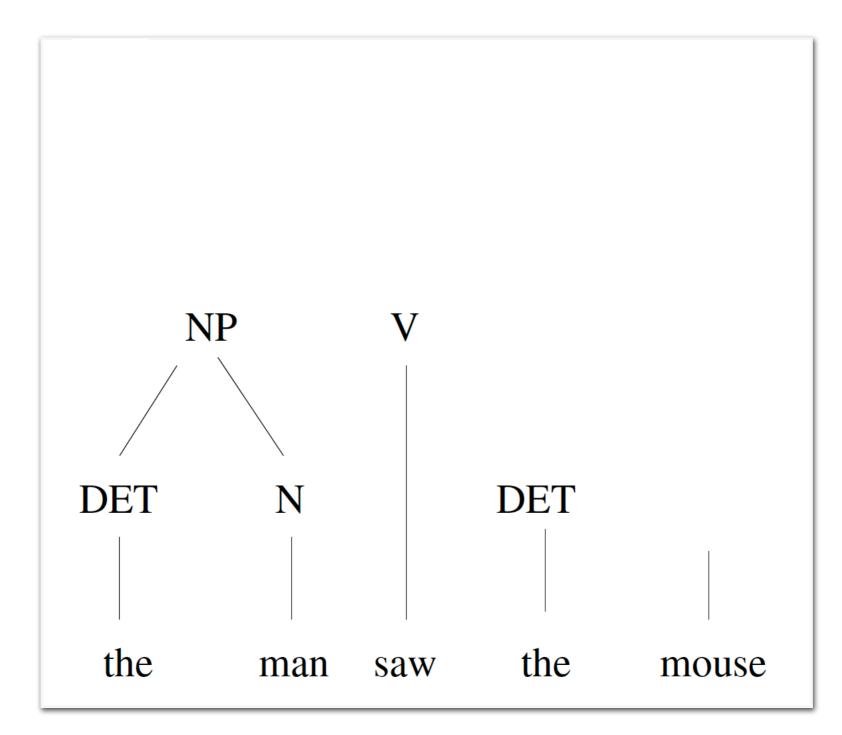




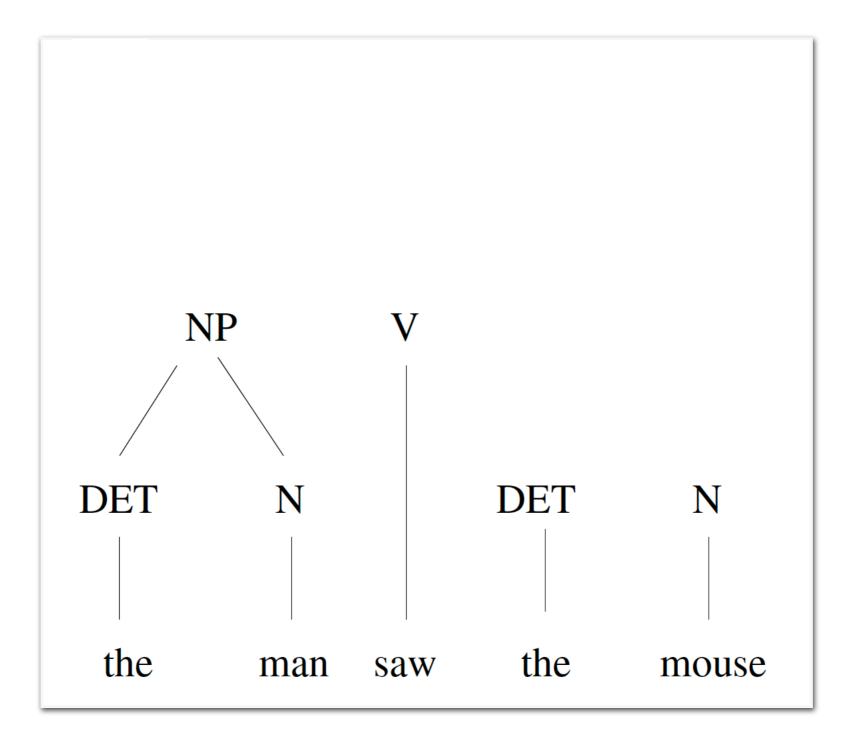




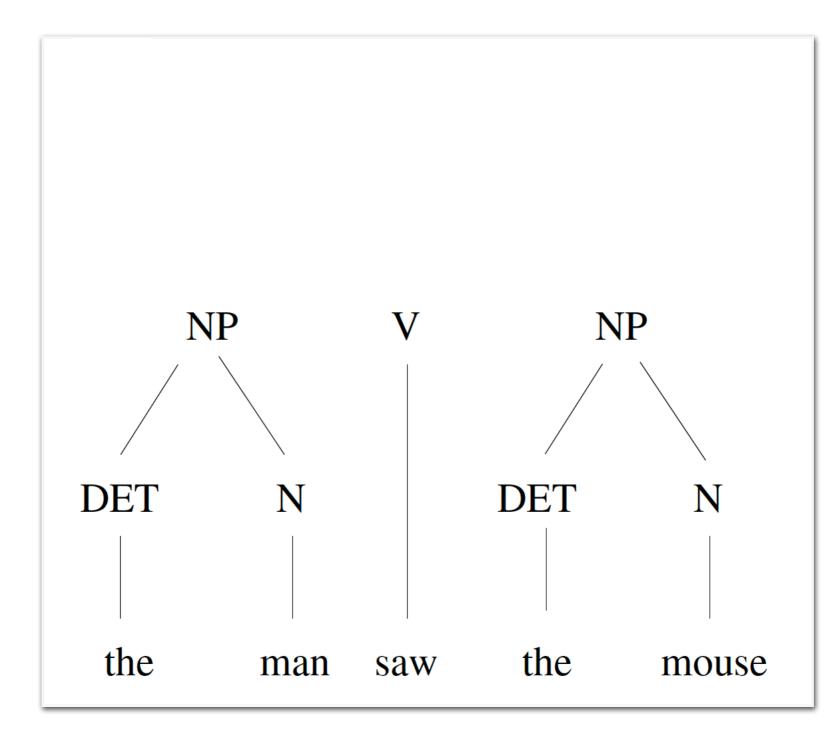




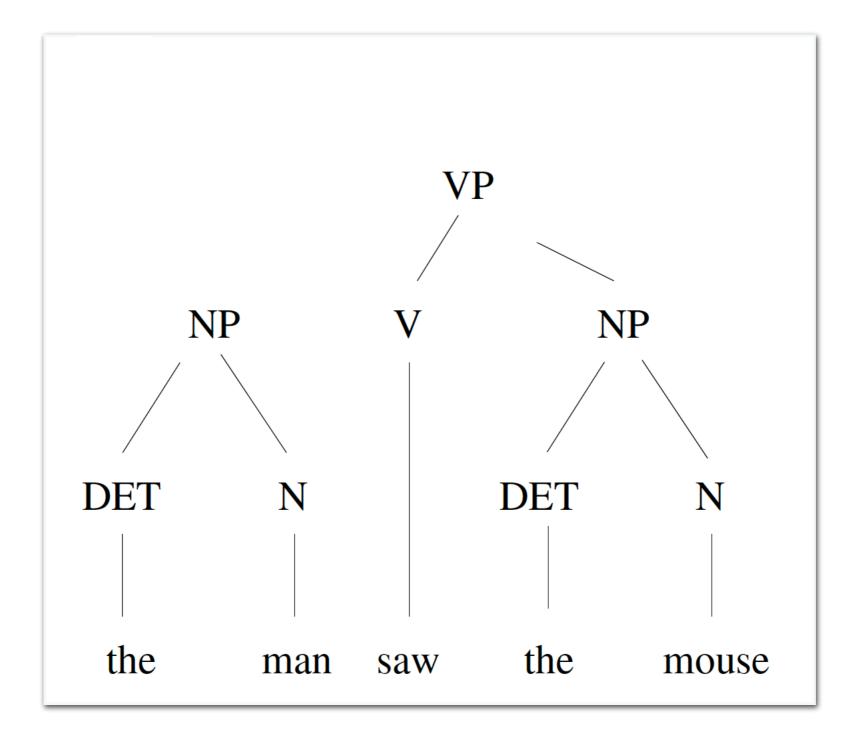




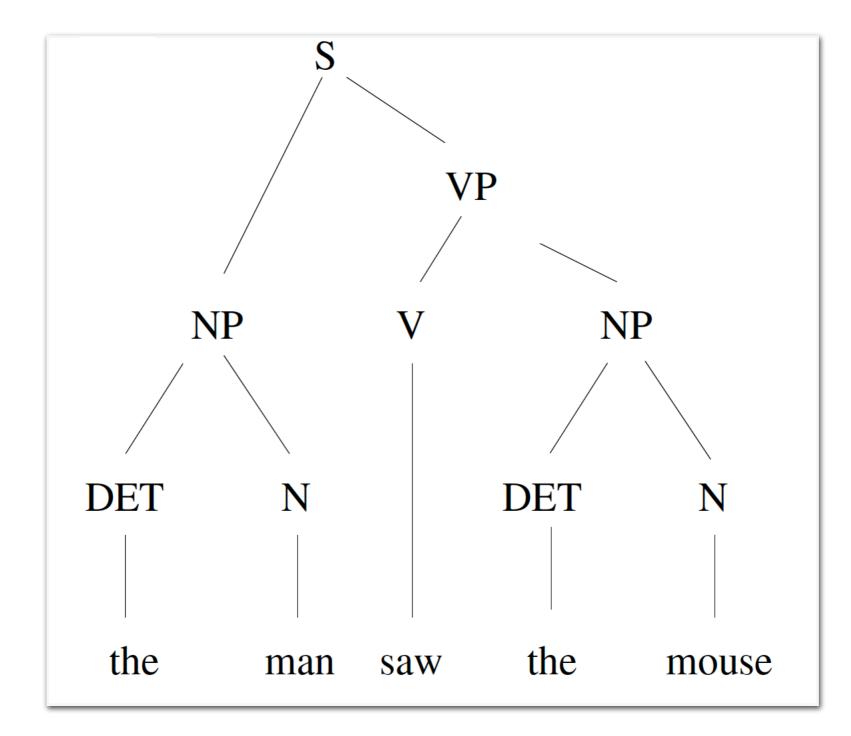














Bottom-Up Parsing - Problems

- ε-production
- Lexical ambiguity



Chart Parsing - Motivation

- Problems with top-down and bottom-up parsers, e.g.:
 - ▶ Left recursion
 - Ambiguity (structural, lexical category etc.)
 - Inefficiency (backtracking)



Chart Parsing - Strategy

- Record all partial parses
- Build up subtrees and keep them in a table (chart)
- Keep only one instance of each chart entry
- Chart entries are never deleted
- No backtracking
- End of the sentence: chart contains all possible parses
- Example algorithms: *Earley* algorithm (top-down);
 CKY algorithm (bottom-up)



Earley Algorithm - Overview

- Left-to-right top-down parsing
- Chart entries (dotted rules) consist of:
 - Subtree corresponding to a grammar rule
 - Information about how much of this rule has been found
 - Position of subtree in respect to input
- Three operators:
 - Predictor
 - Scanner
 - Completer
- See detailed examples in the book



Earley Algorithm -Examples (Chart Entries)



Earley Algorithm - Example

Input Sentence
the man saw the mouse
Parsing Steps
1. Predictions
S> . NP VP [0,0] NP> . DET N [0,0]
2. Scanning DET> the . [0,1]
3. Completion NP> DET . N [0,1]
4. Scanning N> man . [1,2]

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Earley Algorithm - Example (Step by Step)

>>> >>> nltk.app.chartparser() grammar= ((' ', 'S -> NP VP,')	cke — python –	- 107×27						
(' ', 'VP -> VP PP,') (' ', 'VP -> V NP,')				Chart Parser Applicat	ion			
<pre>(' ', 'VP -> V,') (' ', 'NP -> Det N,') (' ', 'NP -> NP PP,') (' ', 'PP -> P NP,') (' ', "NP -> 'John',") (' ', "NP -> 'I',") (' ', "Det -> 'the',") (' ', "Det -> 'my',") (' ', "Det -> 'a',")</pre>	NP	S VP						
<pre>(' ', "N -> 'dog',") (' ', "N -> 'cookie',") (' ', "N -> 'table',") (' ', "N -> 'cake',") (' ', "V -> 'ate',") (' ', "V -> 'saw',") (' ', "P -> 'on',") (' ', "P -> 'under',") (' ', "P -> 'with',")) tokens = ['John', 'ate', 'the', 'cake', 'on', Calling "ChartParserApp(grammar, tokens)"</pre>	'John' NP • Det N NP • NP PP NP • U'John' NP • U'l' Det • U'the' Det • U'the' Det • U'the' NP v'John'	'ate'	"the'	'cake'	'on'	"the"	table'	
		Down Init Top Do Rule Down Bottom Up	wn Predict B Rule	Bottom Up Predict Rule	Bottom Up Left Predict R		Indamental Rule Reset Parser	✓ Step



Earley Algorithm - Example (Step by Step)

- Try it out yourself! (via NLTK)
- Also try the bottom-up chart parser (CKY)



Adding Probabilities to our Grammar



Probabilistic Parsing: Motivation

- Ambiguity, but some parses are more likely than others
- Augment context-free grammars with additional knowledge (probabilities for each rule)
- Where do we get these probabilities from?
- Find the most likely parse

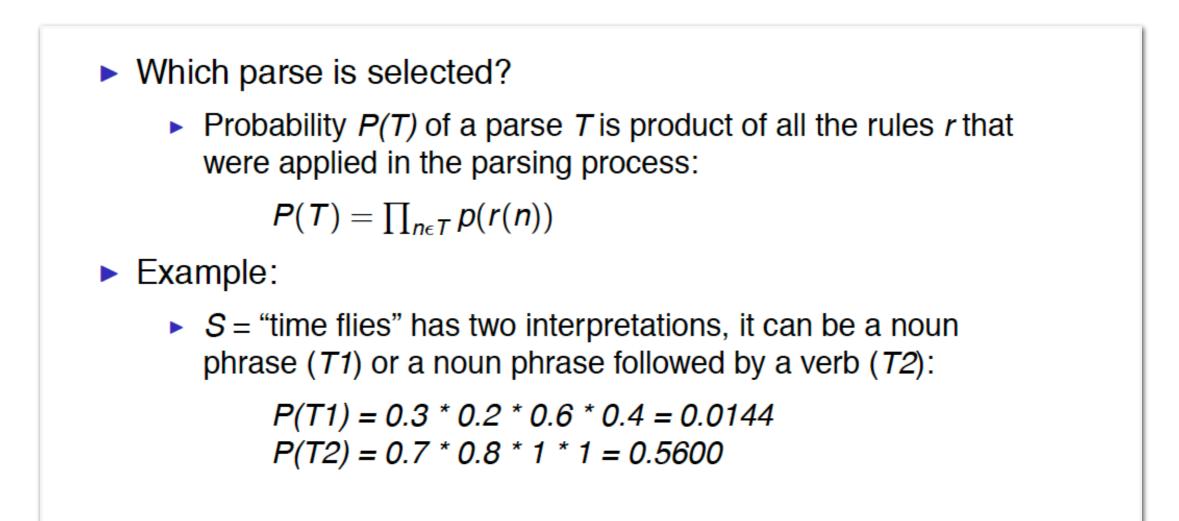


Probabilistic Parsing: Example

S --> NP VP [0.7]S --> NP [0.3]NP --> N [0.8]NP --> N N [0.2] $N \rightarrow flies [0.4]$ N --> time [0.6] VP --> V [1.00]V --> flies [1.00]



Probabilistic Parsing





Probabilistic Parsing

- Obtaining Probabilities
 - Analyze annotated corpus (treebank) or
 - Create statistics by parsing sample corpus
- Parsing of Probabilistic CFG
 - Same principles as with any CFG
 - Calculate probabilities during parsing
 - Optimization (e.g. pruning of unlikely parses)



Probabilistic Parsing

• Problems

- Usual problems with statistical approaches
- Independence assumption
- Structural dependencies
- Lexical dependencies
- Solutions
 - Incorporate additional knowledge
 - Probabilistic lexicalized CFG
 - Chart parsers can easily be adjusted (see textbook)



Probabilistic Parsing: Summary

- Probabilities can help reducing the ambiguity problem
- Combination of symbolic and stochastic ideas
- Chart parsers can easily be adjusted (see textbook)
- There is a lot more to probabilistic parsing and we have only touched the surface



Adding Semantics

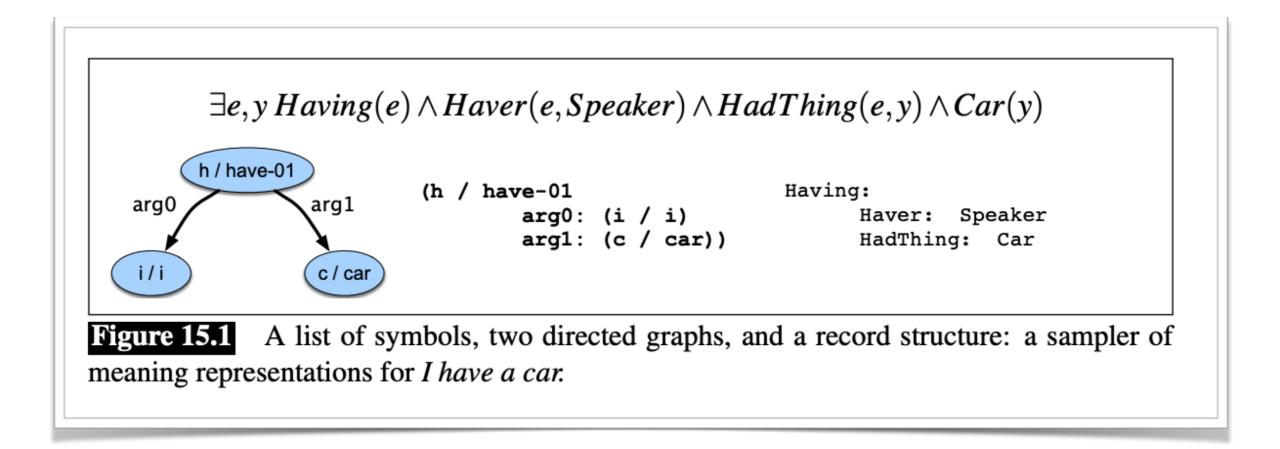


Meaning Representation

- So far concerned with syntax (structure)
- How do we capture semantics (meaning)?



Meaning Representation (Example)





Meaning Representation (Examples)

(1) I need a plumber with no call out fee.
(2) I want to buy a camera for less than 200 Pounds.
(3) Do all taxi companies in Colchester take Visa?
(4) I want to book a restaurant for tomorrow.
(5) Is Maria a lecturer?
(6) Who is Maria?



Semantics: What do we need?

- Represent meaning of natural language (semantics)
- Meaning of words and their relations (lexical semantics)
- Meaning of phrases, sentences, questions (compositional semantics)
- Logical form as a result of semantic interpretation



Semantics: What do we need it for?

- Question answering (QA) systems (recall MIT START)
- Query databases (knowledge bases)
- Precise data representation
- Dialogue understanding
- Intelligent coffee machine?
- . .



Semantics: Requirements

• Verifiability, e.g.:

(15.1) Does Maharani serve vegetarian food?

- Unambiguous representation
- Canonical form, e.g.:

(15.4) Does Maharani have vegetarian dishes?

(15.5) Do they have vegetarian food at Maharani?

(15.6) Are vegetarian dishes served at Maharani?

(15.7) Does Maharani serve vegetarian fare?

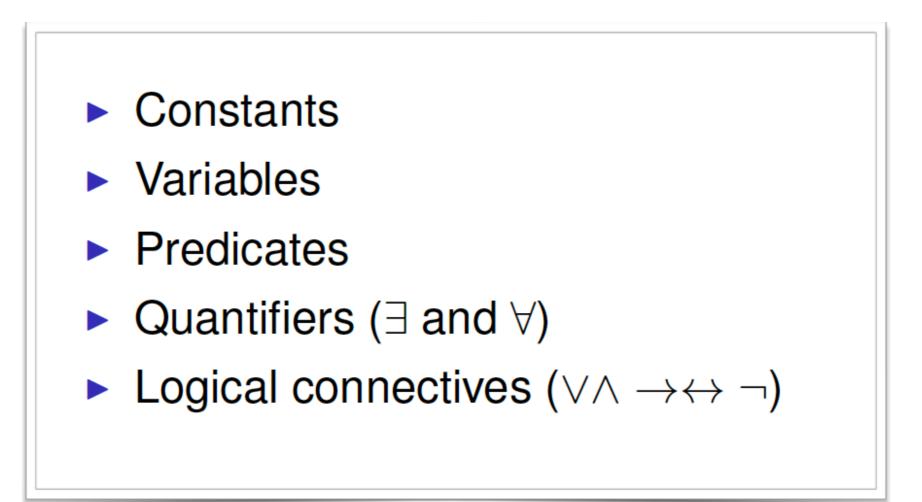
- Inference and variables
- Expressiveness
- Combine syntax and semantics

First Order Predicate Calculus (FOPC) Universität Regensburg

- Mathematical formalism to represent meaning
- Represent objects, properties of objects and relations among them (set of symbols and rules for combining them into terms)
- Inference rules
- Inference purely formal manipulation of symbols (no meaning or interpretation assigned to symbols)
- Meaning introduced by referencing to objects
- Set of terms (axioms) to represent some world model
- Terms in world model are true
- All formulae are either true or false (in respect to the model)



FOPC: Elements





FOPC: Examples

lecturer(maria) isa(maria, lecturer)

 $\forall x (taxi_company(x) \land located(x, colchester)) \rightarrow accept(x, visa)) \\ \forall x taxi_company_in_colchester(x) \rightarrow accept(x, visa))$



Why is FOPC useful?

- Tractable and well-understood
- Flexible, easy to use
- Sufficient for many (simple) applications
- Inference (e.g.modus ponens)
- Structure of language can be mapped onto FOPC expressions, e.g. verbs + subcategorization



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But ...

Any employee in the public sector whose position is at least 50 % suitable for working in home-office should, as a basic principle, be granted the right to work completely in home-office, should they want this and should the necessary technical infrastructure be available.

The Federal Office for Family and Civil Tasks (Bundesamt für Familie und zivilgesellschaftliche Aufgaben (BAFzA)) has released a PDF document containing general information on the effects of SARS-CoV-2 in pregnancy and while breast feeding, and with information on the laws protecting mothers: <u>download the PDF from the BAFyA website</u> - (German version)



FOPC: Problems

- Vague information
- Representation of belief
- Representation of events and time
- Discourse resolution



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Problems with FOPC: Ways Out

- Extensions to FOPC
- Higher-order logics
- Modal logics



Combining Syntax and Semantics

- Syntax-driven semantic analysis
- Grammar rules combine syntax and semantics
- Semantics just an additional feature in feature-structurebased grammar
- Lexical items and rules are associated with logical forms
- Semantic information is passed from children to parents
- Need extension of FOPC to handle "incomplete" expressions: *λ*-calculus and complex terms to build quasi-logical forms



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Examples

(1) I like Scotland. \rightarrow like(speaker, scotland) (2) I sleep. \rightarrow sleep(speaker) (3) All students sleep. \rightarrow $\forall x(isa(x, student) \rightarrow sleep(x))$ (4) sleep $\rightarrow \lambda x$ sleep(x) (5) like $\rightarrow \lambda x \lambda y$ like(y, x) (5) like Scotland $\rightarrow \lambda y$ like(y, scotland)



Simplified Example Grammar

S --> NP VP {VP.sem(NP.sem)} VP --> V {V.sem} VP --> V NP {V.sem(NP.sem)} NP --> 'i' {speaker} NP --> 'scotland' {scotland} V --> 'sleep' $\{\lambda x \text{ sleep}(x)\}$ V --> 'like' $\{\lambda x, \lambda y \text{ like}(y, x)\}$

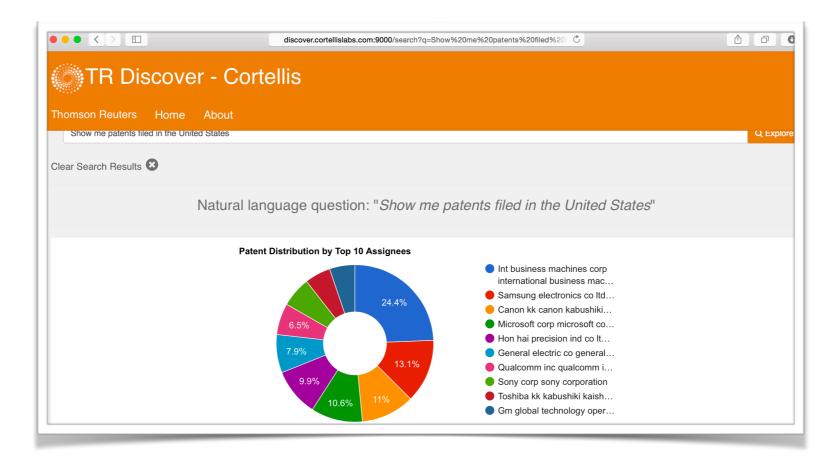


Simplified Example Grammar

S --> NP VP {VP.sem(NP.sem)} VP --> V {V.sem} NP --> DET N {<DET.sem x isa(x,N.sem)>} NP --> 'i' {speaker} DET --> 'all' $\{\forall\}$ N --> 'students' {student} V --> 'sleep' $\{\lambda \times \text{sleep}(\mathbf{x})\}$

Real Example: TR Discover by Universität Regensburg Thomson Reuters

- Natural language questions over complex datasets
- Combination of syntax and semantics
- Based on context-free grammars
- Use of FOPC to encode semantics





TR Discover: Sample Rules

```
N[TYPE=drug, NUM=pl, SEM=<λx.drug(x)>]
--> `drugs'
V[TYPE=[org, drug],
SEM=λXx.X(λy.develop_org_drug(x,y))>,
TNS=prog, NUM=?n]
--> `developing'
```

D. Song et al. "Natural Language Question Answering and Analytics for Diverse and Interlinked Datasets". Proceedings of NAACL-HLT 2015.



Problems (Compositional Approach)

- Natural language is not mathematics
- Idioms
- Ambiguity, e.g. quantifier scoping
- Compositional approach does not tell us anything about individual meaning of words
- Usual problems with symbolic approaches



Summary Meaning Representation

- Expressing meaning of natural language is very difficult
- FOPC can be a good approximation
- Other logics are needed to express phenomena like time, beliefs etc.
- λ calculus permits syntax-driven semantic analysis



Language and Complexity

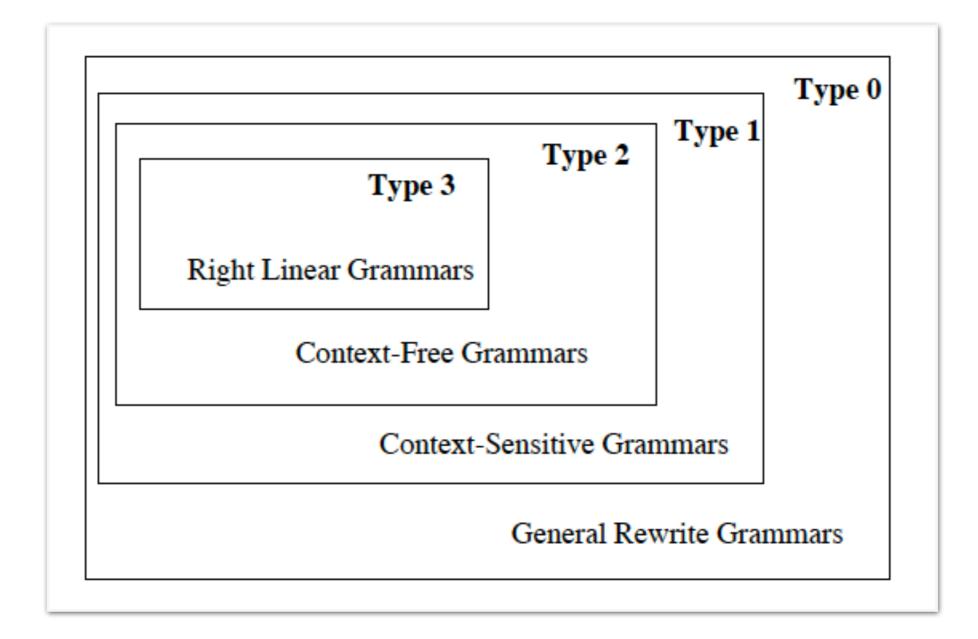
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Language and Complexity: Motivation

- Complexity is a major issue in computer science
- The complexity of languages can be defined by the type of grammar they require
- The Chomsky hierarchy defines four types of grammar (the higher the complexity the lower the number)
- Certain constructions in languages require certain types of grammar
- The types of grammar correspond to different types of automata
- This allows reasoning about mathemetical complexity



Chomsky Hierarchy





Grammars vs. Automata

Туре	Grammar	Rule Type
0	General rewrite	$\alpha - > \beta$
1	Context-sensitive	$\beta A \gamma - > \beta \delta \gamma$
2	Context-free	$A - > \beta$
3	Right linear	A - > xB, A - > x

(A and B are nonterminals, x is a string of terminals, α , β , γ , δ are strings of terminals and nonterminals (δ not being empty))



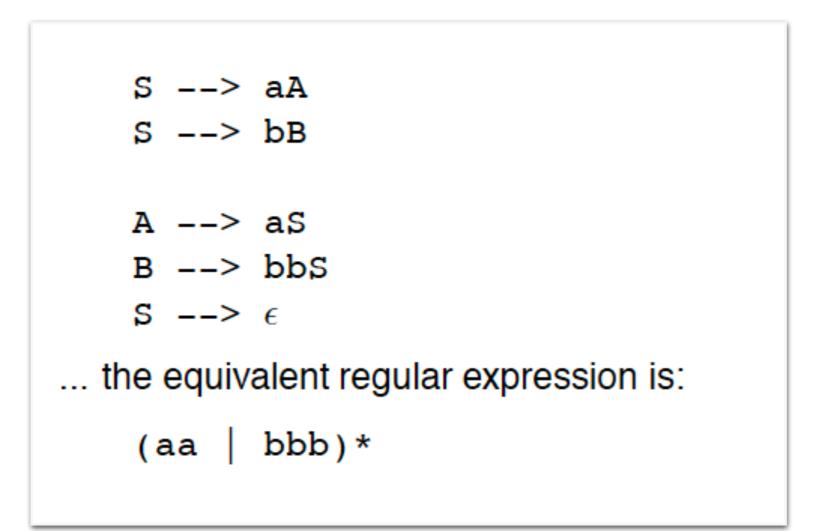
Grammars vs. Automata II

Туре	Automaton	Memory
0	Turing Machine	Unbounded
1	Linear Bounded (LBA)	Bounded
2	Push Down (PDA)	Stack
3	Finite State (FSA)	None



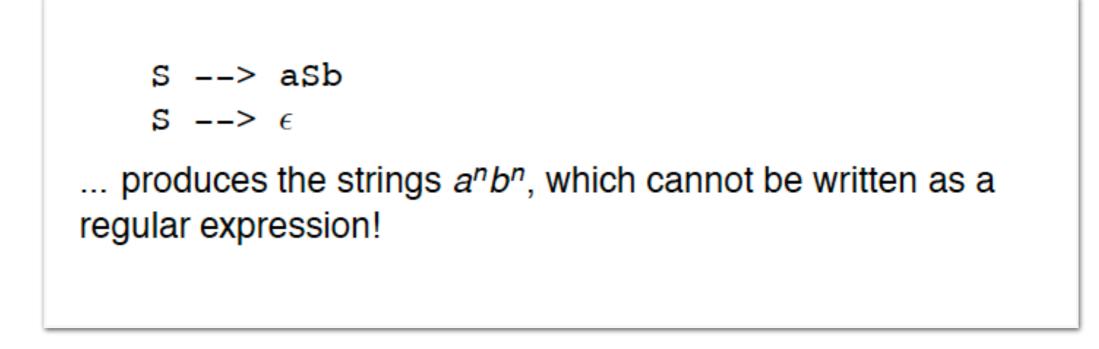
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Example 1: Right Linear Grammar





Example 2: Context-Free Grammar





Example 3: Context-Sensitive Grammar

S --> aSBC S --> abC bB --> bb bC --> bc cC --> cc CB --> BC

... produces the strings *aⁿbⁿcⁿ*, which cannot be written as a context-free grammar!

Natural Languages in the Chomsky Hierarchy



- Are natural languages regular?
- Not really as they often come with patterns that correspond to languages like <u>a</u>ⁿbⁿ
- Centre-embedding, for example, causes languages to be non-regular:
 - The student likes the Meetup.
 - The student the student likes likes the Meetup.
 - The student the student the student likes likes the Meetup.
- Certain natural languages are not even context-free
- Fair enough, this is all a bit hypothetical ...



Complexity of Grammar Types

- Measure the amount of work to decide whether a string is in a given language or not
- Cost as a function of input length (n)
- Worst case scenarios

Туре	Grammar	Complexity
0	General rewrite	undecidable
1	Context-sensitive	e ⁿ (exponential)
2	Context-free	n ³ (cubic)
3	Right linear	n (linear)

... that makes grammars of type 0 and 1 not attractive to computer scientists

Complexity of Parsing



- So far we looked at the decision problem
- Parsing is more complex
- Example:

 $S \longrightarrow X$ $S \longrightarrow Y$ $S \longrightarrow \epsilon$ $X \longrightarrow aS$ $Y \longrightarrow aS$

- Number of possible parse trees for this grammar is exponential (2ⁿ)
- Enumerating all possible parse trees therefore even for type 3 grammars exponential



Summary

- Languages can be defined by means of grammars or automata
- Parsers return tree structure(s) of some input given a grammar
- First-order predicate calculus is a basis for simple meaning representation
- Knowledge about grammar allows to reason about mathematical complexity
- All this is a *knowledge-based* approach, i.e. at the other end of the spectrum of *embeddings*





- Jurafsky and Martin (2020), chapters 13-15 and Appendix C
- The third edition focuses on the CKY parser only, the second edition has both Earley and CKY with running examples
- Jurafsky and Martin (second edition), chapter 16 discusses complexity
- D. Song, F. Schilder, C. Smiley and C. Brew. "Natural Language Question Answering and Analytics for Diverse and Interlinked Datasets". Proceedings of NAACL-HLT 2015.
- See previous slide deck for links to parsers