Natural Language Processing

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CSE 352 — Artificial Intelligence
Prof. Anita Wasiewska
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Works Cited

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Outline

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- Of course, questions are welcome at any time.

How Do We Think About Language?

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- How?

Generative Grammar

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- In Noam Chomsky's *Syntactic Structures* (1957), he claims that we cannot use word chains, databases or other similar devices.
- Instead, we need to have a set of rules (a grammar) that can generate any sentence that speakers can produce.
- This lead to the creation of what we computer scientists call a context-free grammar.

What is a Context-Free Grammar?

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- This is the grammar that generates all matched lists of parentheses.

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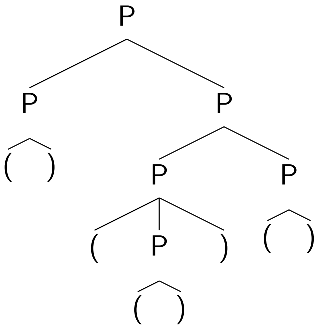
  (Carnie 175)
- Let's explore the meaning of this grammar via means of analogy.

Derivation Tree for ()(())()

- 

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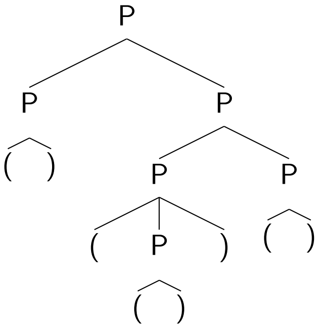
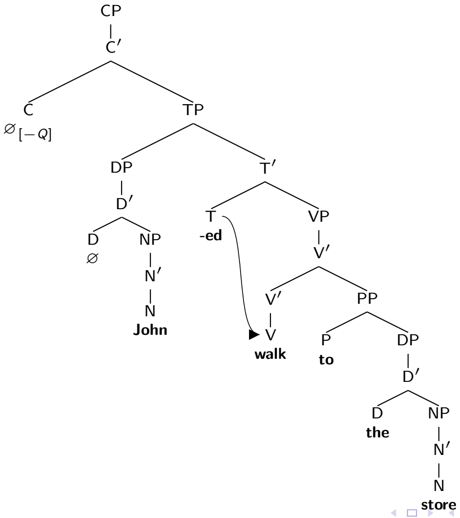
- 

- This is just one of several ways of deriving this statement — hence this is an ambiguous grammar.

Derivation Tree for an English Sentence

- 

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- For simple grammars we can use a stack-based implementation — for example, the parethesis-matching grammar above can be recognized by pushing every left parenthesis on the stack, and popping off a parenthesis when a right parenthesis is read.
- However, this strategy leads to nondeterministic behavior in general. We will need a more powerful computational tool. (Sipser 115)

Dynamic Programming and Context-Free Grammars

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- We do this by *memoizing* the results of the recurrence, so that when it is called again with the same arguments, we can just do a constant-time table lookup instead of repeating a lengthy computation.
- But what should our recurrence be? Although CFGs exhibit recursion, they don't immediately lend themselves to an intuitive recurrence.

Chomsky Normal Form

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- Fortunately, natural language is already in a Chomsky Normal Form.

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- If we try to parse a string using the rule $X \rightarrow YZ$ and the string is in the grammar $((M(1, n, X)))$, then it must be the case that $\exists i (1 \leq i < n) \wedge (M(1, i, Y) \wedge M(i + 1, n, Z))$.

The Algorithm

- With these two rules, we can now create our dynamic programming array:

$$M[i,j,X] = \bigvee_{(X \to YZ) \in G} \left(\bigvee_{k=i}^{j} M[i,k,Y] \cdot M[k+1,j,Z] \right)$$

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- Since it takes linear time to evaluate each cell in the array, and there are n^2 cells, evaluating $M(1,n,S)$, where S is the start symbol of the grammar, takes $\mathcal{O}(n^3)$ time.

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- There are a number of technical difficulties in writing a language parser. Notably, there are many times where nodes point to words that are phonologically null, or do not exist depending on the context.
- Additionally, words move around in the tree, such as in the case of Subject-Aux Inversion, and tense modifiers for verbs attach at a different point in the tree.

More Problems with Language Processing

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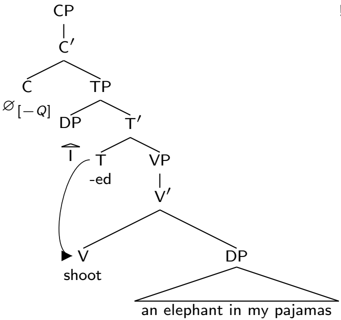
- The more significant problems is that natural language is inherently ambiguous; Groucho Marx's quip "I shot an elephant in my pajamas" comes to mind.
- Even in syntactically unambiguous sentences, there can exist semantic ambiguities that make the meaning of the sentence unclear.

Syntactic Ambiguities



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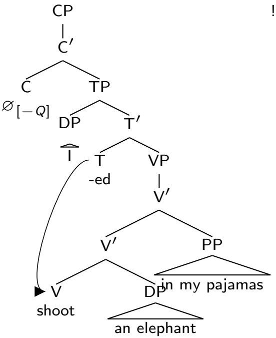

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  - "We gave [the monkeys]$_i$ [the bananas]$_j$ because [they]$_j$ were ripe."
- While these two sentences have identical syntax trees, the pronoun "they" is *bound* to two different phrases in the two different sentences. (SpecGram)

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- Any of these bindings can be correct.

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- Problems like the ones just mentioned are known as *NLP-hard* problems; that is, solving these problems requires at least a program capable of fully understanding natural language.
- Of course, this doesn't stop researchers from trying to crack the problems of language.
- There are quite a number of subproblems, other areas of research, and other interesting things to study when it comes to natural language.

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- These parsers are often supplemented with corpuses (large bodies of text) that can aid in computing the probabilities of each rule.

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- Speech recognition is still certainly an open problem — programs can recognize a small number of words spoken by a large number of people, or a large number of words spoken by a small number of people, but not both.
- Anyone who has seen the infamous Windows Vista speech recognition demo knows that there is a lot that can go wrong.

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- From there, we can feed the model sets of preworked data, from which it can build the probabilities.
- Intuitively, this makes sense — certain phoneme sequences like [kn] are just not very likely, and we can exploit that to eliminate those types of possibilities *en masse*. (Rabiner)

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- Obviously this is one of the harder problems facing NLP, and while there have been a number of commmercial efforts, none have been particularly successful.

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- In other cases, information is lost in translation. Romance languages are especially notorious for omitting subject pronouns before verbs, which causes gender to be lost.
- Because of these difficulties, machine translation most likely requires a tool capable of completely understanding a language.

News and Blog Analysis with Lydia

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- The goals of Lydia include the automatically spidering of news stories and their correlate them based on common terms and ideas, as well as identifying subjectivity in news stories.

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- Then a wordmap of positive and negative adjectives could be built. For each day, the number of positive and negative adjectives concerning a particular concept (in this case Korea) was counted.

Analyzing Subjectivity

- Finally, for a given language l, day d, and entity e, the subjectivity could be calculated as:

$$\frac{pos\_references_{l,e,d} - neg\_references_{l,e,d}}{num_occurences\_l, e, d}$$

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- The results of running this experiment for a week returned expected results; Korean had the highest subjectivity score, while Japan was among the lowest, and the several European countries sampled were in the middle. (Bautin et al)