Exercise Loday!

Context-Free Grammars

CS 485, Fall 2023
Applications of Natural Language Processing https://people.cs.umass.edu/~brenocon/cs485_f23/

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College of Information and Computer Sciences University of Massachusetts Amherst Syntax: how do words structurally combine to form sentences and meaning?

2 sprepentations

- Constituents
 - [the big dogs] chase cats
 - [colorless green clouds]/chase cats
- Dependencies
 - The dog chased the cat.
 - My dog, who's getting old, chased the cat.

- Idea of a grammar (G): global template for how sentences / utterances / phrases w are formed, via latent syntactic structure y
 - Linguistics: what do G and P(w,y | G) look like?
 - Generation: score with, or sample from, P(w, y | G)
 - Parsing: predict P(y | w, G)

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Syntax for NLP

- If we could predict syntactic structure from raw text (parsing), that could help with...
 - Language understanding: meaning formed from structure
 - Grammar checking
 - Preprocessing: Extract phrases and semantic relationships between words for features, viewing, etc.
- Provides a connection between the theory of generative linguistics and computational modeling of language
- Accurate full sentence parsing is challenging!

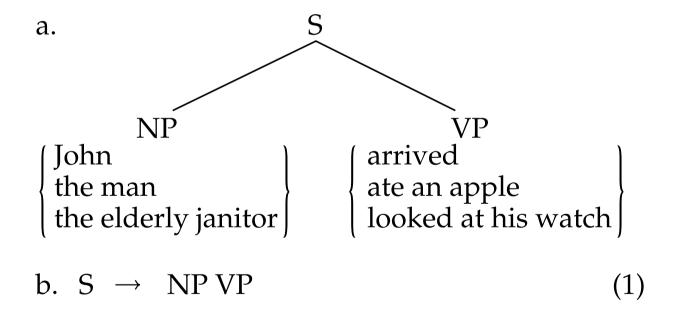


Is language context-free?

- Regular language: repetition of repeated structures
 - e.g. "base noun phrases": (Noun | Adj)* Noun
 - subset of the JK pattern
- Context-free: hierarchical recursion
- Center-embedding: classic theoretical argument for CFG vs. regular languages
 - (10.1) The cat is fat.
 - (10.2) The cat that the dog chased is fat.
 - (10.3) *The cat that the dog is fat.
 - (10.4) The cat that the dog that the monkey kissed chased is fat.
 - (10.5) *The cat that the dog that the monkey chased is fat.
- Competence vs. Performance

Hierarchical view of syntax

• "a Sentence made of Noun Phrase followed by a Verb Phrase"



Context-free grammars (CFG)

• A CFG is a 4-tuple:

```
N a set of non-terminals \Sigma a set of terminals (distinct from N) R a set of productions, each of the form A \to \beta, where A \in N and \beta \in (\Sigma \cup N)^* S a designated start symbol
```

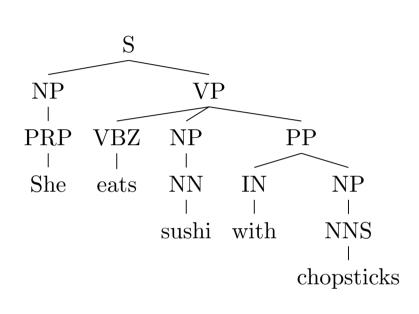
Example: see handout!

- Derivation: a sequence of rewrite steps from S to a string (sequence of terminals, i.e. words)
- Yield: the final string (sentence)
- The parse tree or constituency tree corresponds to the rewrite steps that were used to derive the string

- A CFG is a "boolean language model"
 - A grammar (4-tuple) defines to a set of strings it could generate

• Example: derivation from worksheet's grammar

sushi with NNS Example chopsticks



```
S
NP
             VP
PRP
      VBZ
                  NP
She
                        PP
             NP
      eats
             NN
                            NP
                    IN
            sushi
                   with
                            NNS
                         chopsticks
```

- All useful grammars are ambiguoux Phultiple derivations with same yield
- [Parse tree representations: Nested parens or non-terminal spans]

She eats NN IN NP

[Examples from <u>Fisenstein (2017)</u>]

Constituents

- Constituent tree/parse is one representation of sentence's syntax. What should be considered a constituent, or constituents of the same category?
 - Movement tests
 - Substitution tests
 - Coordination tests
- Simple grammar of English
 - Must balance overgeneration versus undergeneration
 - Noun phrases
 - NP modification: adjectives, PPs
 - Verb phrases
 - Coordination
 - etc...
- Better coverage: machine-learned grammars, if you have a treebank (labeled dataset)

Is language context-free?

- CFGs nicely explain nesting and agreement (if you stuff grammatical features into the nonterminals)
 - The **processor** <u>has</u> 10 million times fewer transistors on it than todays typical microprocessors, <u>runs</u> much more slowly, and <u>operates</u> at five times the voltage...
 - $S \rightarrow NN VP$ $VP \rightarrow VP3S \mid VPN3S \mid ...$ $VP3S \rightarrow VP3S, VP3S, and VP3S \mid VBZ \mid VBZ NP \mid ...$

Real sentences have massively ambiguous syntax!

Attachment ambiguity we eat sushi with chopsticks, I shot an elephant in my pajamas.

Modifier scope *southern food store*

Particle versus preposition *The puppy tore up the staircase.*

Complement structure *The tourists objected to the guide that they couldn't hear.*

Coordination scope "I see," said the blind man, as he picked up the hammer and saw.

Multiple gap constructions The chicken is ready to eat

```
( (S
    (NP-SBJ (NNP General) (NNP Electric) (NNP Co.) )
    (VP (VBD said)
      (SBAR (-NONE- 0)
        (S
          (NP-SBJ (PRP it) )
          (VP (VBD signed)
            (NP
              (NP (DT a) (NN contract) )
              (PP (-NONE- *ICH*-3) ))
            (PP (IN with)
              (NP
                (NP (DT the) (NNS developers) )
                (PP (IN of)
                  (NP (DT the) (NNP Ocean) (NNP State) (NNP Power) (NN project) ))))
            (PP-3 (IN for)
              (NP
                (NP (DT the) (JJ second) (NN phase) )
                (PP (IN of)
                  (NP
                    (NP (DT an) (JJ independent)
                       (ADJP
                         (QP ($ $) (CD 400) (CD million) )
                         (-NONE- *U*) )
                       (NN power) (NN plant) )
                     (,,)
                     (SBAR
                       (WHNP-2 (WDT which))
                       (S
                         (NP-SBJ-1 (-NONE- *T*-2) )
                         (VP (VBZ is)
                           (VP (VBG being)
                             (VP (VBN built)
                               (NP (-NONE- *-1) )
                               (PP-LOC (IN in)
                                 (NP
                                   (NP (NNP Burrillville) )
                                   (,,)
                                   (NP (NNP R.I) )))))))))))))))
```

Penn Treebank

Context-Free Grammar

- CFG describes a generative process for an (infinite) set of strings
 - I. Nonterminal symbols
 - "S": START symbol / "Sentence" symbol
 - 2.Terminal symbols: word vocabulary
 - 3. Rules (a.k.a. Productions). Practically, two types:

"Grammar": one NT expands to >= 1 NT always one NT on left side of rule

```
S \rightarrow NP VP
                               I + want a morning flight
     NP \rightarrow Pronoun
                             Los Angeles
             Proper-Noun
             Det Nominal
                               a + flight
Nominal → Nominal Noun
                               morning + flight
                               flights
              Noun
     VP \rightarrow Verb
                               do
              Verb NP
                               want + a flight
              Verb NP PP
                               leave + Boston + in the morning
              Verb PP
                               leaving + on Thursday
     PP \rightarrow Preposition NP
                               from + Los Angeles
```

Lexicon: NT expands to a terminal

```
Noun 
ightharpoonup flights | breeze | trip | morning | \dots Verb 
ightharpoonup is | prefer | like | need | want | fly Adjective 
ightharpoonup cheapest | non - stop | first | latest | other | direct | \dots Pronoun 
ightharpoonup me | I | you | it | \dots Proper-Noun 
ightharpoonup Alaska | Baltimore | Los Angeles | Chicago | United | American | \dots Determiner 
ightharpoonup the | a | an | this | these | that | \dots Preposition 
ightharpoonup from | to | on | near | \dots Conjunction 
ightharpoonup and | or | but | \dots
```

Probabilistic CFGs

```
S \rightarrow NP VP
                                     [.80]
                                                 Det \to that [.10] \mid a [.30] \mid the [.60]
                                                 Noun \rightarrow book [.10] \mid flight [.30]
S \rightarrow Aux NP VP
                                     [.15]
S \rightarrow VP
                                      [.05]
                                                               meal [.15] | money [.05]
                                                               flights [.40] | dinner [.10]
                                      [.35]
NP \rightarrow Pronoun
NP \rightarrow Proper-Noun
                                      [.30]
                                                 Verb \rightarrow book [.30] \mid include [.30]
NP \rightarrow Det\ Nominal
                                      .20
                                                              | prefer; [.40]
                                                Pronoun \rightarrow I[.40] \mid she[.05]
NP \rightarrow Nominal
                                     [.15]
                                     [.75]
                                                             | me [.15] | you [.40]
Nominal \rightarrow Noun
                                                 Proper-Noun \rightarrow Houston [.60]
Nominal \rightarrow Nominal Noun
                                      [.20]
Nominal \rightarrow Nominal PP
                                     [.05]
                                                               TWA [.40]
                                                 Aux \rightarrow does [.60] | can [40]
                                      [.35]
VP \rightarrow Verb
VP \rightarrow Verb NP
                                      .20
                                                 Preposition \rightarrow from [.30] \mid to [.30]
VP \rightarrow Verb NP PP
                                      [.10]
                                                               on [.20] | near [.15]
VP \rightarrow Verb PP
                                     [.15]
                                                               through [.05]
VP \rightarrow Verb NP NP
                                      [.05]
VP \rightarrow VP PP
                                     [.15]
                                     [1.0]
PP \rightarrow Preposition NP
```

- Defines a probabilistic generative process for words in a sentence
 - Can parse with a modified form of CKY
- How to learn? Fully supervised with a treebank... unsupervised learning possible too, but doesn't give great results...
 []&M textbook]

PCFG as LM

Is a PCFG a good LM? Yes...

Is a PCFG a good LM? No...