Constituency Parsing: CKY

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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:

<u>"Grammar": one NT expands to >=1 NT</u> always one NT on left side of rulep

I + want a morning flight $S \rightarrow NP VP$ $NP \rightarrow Pronoun$ Ι Los Angeles Proper-Noun Det Nominal a + flight Nominal \rightarrow 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

Non-Stight Non-Shreeze

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

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Parsing with a CFG

- Task: given text and a CFG, answer:
- usk: given text and a CFG, answer: Does there exist at least one parse? (=) 75 fbe strong (fact) Enumerate parses (backpointers) 970 mmArit (m HIGCFG)
- Problem: extremely high number of possible trees for a sentence, and even a large number of legal trees (licensed by the grammar) for a sentence
 - Many parsing algorithms have been invented to tackle this
- Cocke-Kasami-Younger algorithm (CKY)
 - Bottom-up dynamic programming: Find possible nonterminals for short spans of sentence, then possible combinations for higher spans
 - Maintains local ambiguity, representing many subtrees for each span. ("Packed forest" representation)
 - Provably finds all possible parse trees (legal derivations), and correctly says when none exist.
 - Requires converting to Chomsky Normal Form (binarization)











Name: _____

Fill in the CYK dynamic programming table to parse the sentence below. In the bottom right corner, draw the two parse trees. Show the possible nonterminals in each cell. Optional: draw the backpointers too.

















Probabilistic CFGs

- $S \rightarrow NP VP$ $Det \to that [.10] \mid a [.30] \mid the [.60]$ [.80] $S \rightarrow Aux NP VP$ [.15] Noun \rightarrow book [.10] | flight [.30] $S \rightarrow VP$ [.05] *meal* [.15] | *money* [.05] [.35] *flights* [.40] | *dinner* [.10] $NP \rightarrow Pronoun$ $NP \rightarrow Proper-Noun$ [.30] $Verb \rightarrow book [.30] \mid include [.30]$ $NP \rightarrow Det Nominal$ [.20] | *prefer*; [.40] *Pronoun* \rightarrow *I*[.40] | *she*[.05] $NP \rightarrow Nominal$ [.15] [.75] | *me* [.15] | *you* [.40] Nominal \rightarrow Noun Nominal \rightarrow Nominal Noun [.20] *Proper-Noun* \rightarrow *Houston* [.60] [.05] *TWA* [.40] Nominal \rightarrow Nominal PP [.35] $VP \rightarrow Verb$ $Aux \rightarrow does [.60] \mid can [40]$ $VP \rightarrow Verb NP$ [.20] Preposition \rightarrow from [.30] | to [.30] on [.20] | near [.15] [.10] $VP \rightarrow Verb NP PP$ through [.05] $VP \rightarrow Verb PP$ [.15] $VP \rightarrow Verb NP NP$ [.05] $VP \rightarrow VP PP$ [.15] $PP \rightarrow Preposition NP$ [1.0]
- Defines a probabilistic generative process for words in a sentence
- (How to learn? Fully supervised with a treebank...)

```
( (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) )
                             (, ,)
```

Penn Treebank

PCFG as LM

Is a PCFG a good LM? Yes...

Is a PCFG a good LM? No...

(P)CFG model, (P)CKY algorithm

- CKY: given CFG and sentence w
 - Does there exist at least one parse?
 - Enumerate parses (backpointers)
- Probabilistic CKY: given PCFG and sentence w
 - Likelihood of sentence P(w)
 - Most probable parse ("Viterbi parse") argmaxy P(y | w) = argmaxy P(y, w)

- Parsing model accuracy: lots of ambiguity!!
 - PCFGs lack lexical information to resolve ambiguities (sneak in world knowledge?)
 - Modern constituent parsers: enrich PCFG with lexical information and fine-grained nonterminals
 - Modern dependency parsers: effectively the same trick
- Parsers' computational efficiency
 - Grammar constant; pruning & heuristic search
 - O(N³) for CKY (ok? depends...)
 - O(N) left-to-right incremental algorithms
- What was the syntactic training data?