Syntax (I)

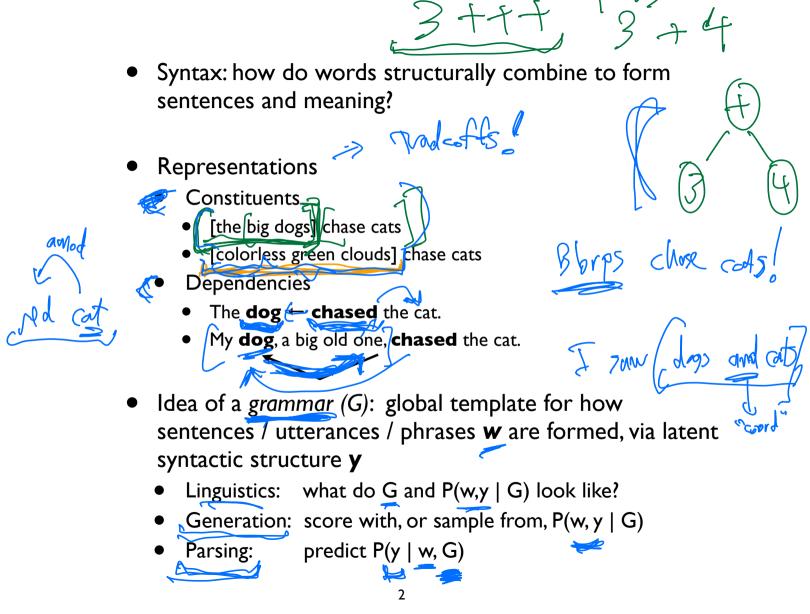
CS 685, Spring 2021

Advanced Topics in Natural Language Processing <u>http://brenocon.com/cs685</u> <u>https://people.cs.umass.edu/~brenocon/cs685_s21/</u>

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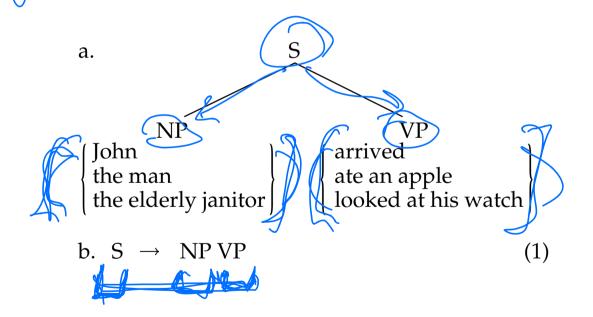
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Hierarchical view of syntax

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

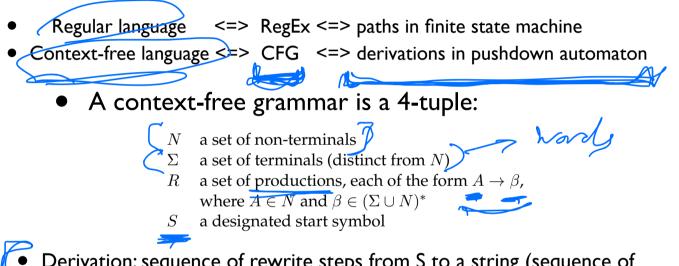


[From Phillips (2003)]

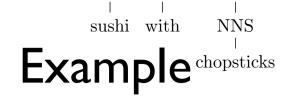
- Seems useful to explain e.g. nesting and agreement
 - The processor has 10 million times fewer transistors on it than todays typical microprocessors, runs much more slowly, and operates at five times the voltage...

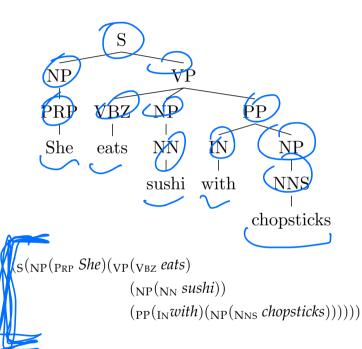
•
$$S \rightarrow NN VP$$

 $VP \rightarrow VP3S | VPN3S | \dots$
 $VP3S \rightarrow VP3S, VP3S, and VP3S | VBZ | VBZ NP | \dots$



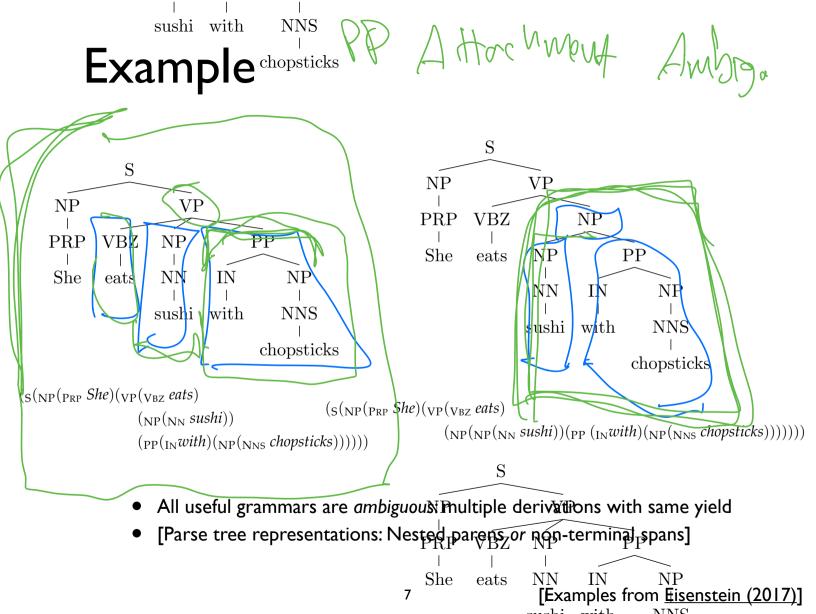
- Derivation: sequence of rewrite steps from S to a string (sequence of terminals, i.e. words)
- Yield: the final string
- A CFG is a "boolean language model"
- A probabilistic CFG is a probabilistic language model:
 - Every production rule has a probability; defines prob dist. over strings.





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

[Examples from Eisenstein (2017)]



Constituents

- Constituent tree/parse is one representation of sentence's syntax. What should be considered a constituent, or constituents of the same category?
 - Substitution tests
 - Pronoun substitution
 - Coordination tests
- Simple grammar of English
 - Must balance overgeneration versus undergeneration
 - Noun phrases



- NP modification: adjectives, PPs
- Verb phrases
- Coordination
- etc...
- Machine-learned grammars of English...

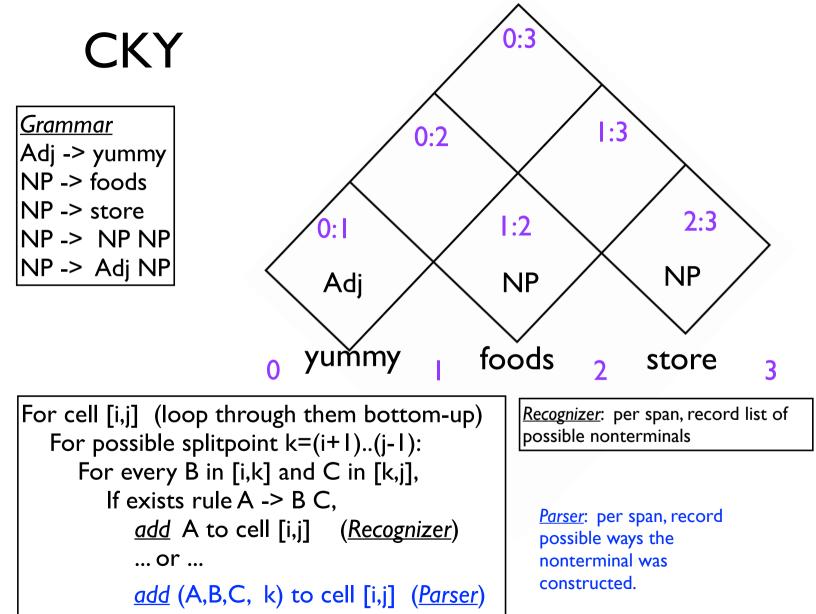
• Ambiguities in syntax

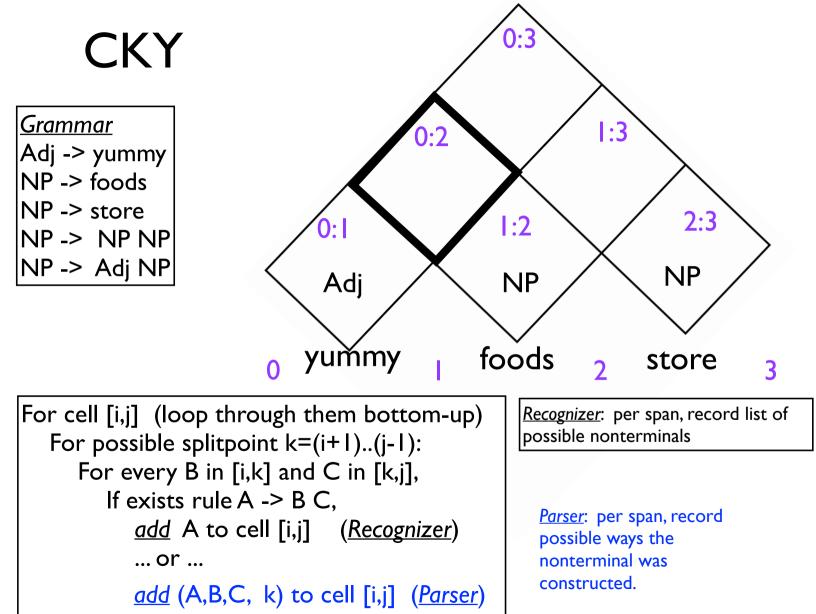
Attachment ambiguity we eat sushi with chopsticks, I shot an elephant in my pajamas.
Modifier scope southern food store
Particle versus preposition The puppy tore up the staircase.
Complement structure The tourists objected to the guide that they couldn't hear.
Coordination scope "I see," said the blind man, as he picked up the hammer and saw.
Multiple gap constructions The chicken is ready to eat

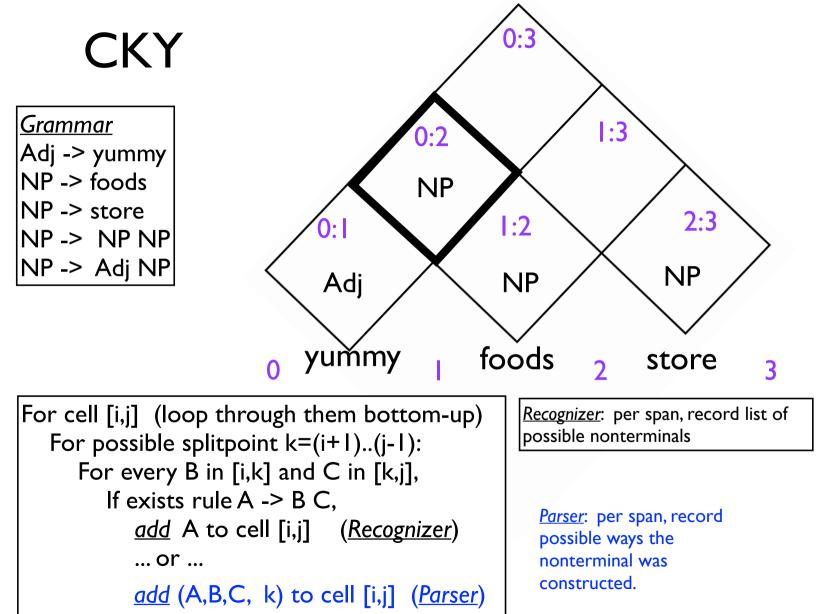
Parsing with a CFG

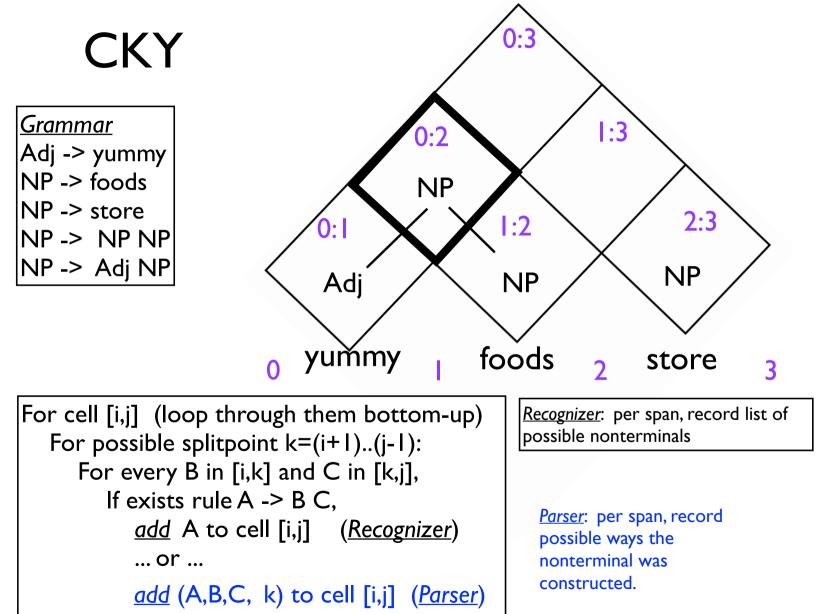
- Task: given text and a CFG, answer:
 - Does there exist at least one parse?
 - Enumerate parses (backpointers)
- Cocke-Kasami-Younger algorithm
 - Bottom-up dynamic programming: Find possible nonterminals for short spans of sentence, then possible combinations for higher spans
 - Requires converting CFG to Chomsky Normal Form

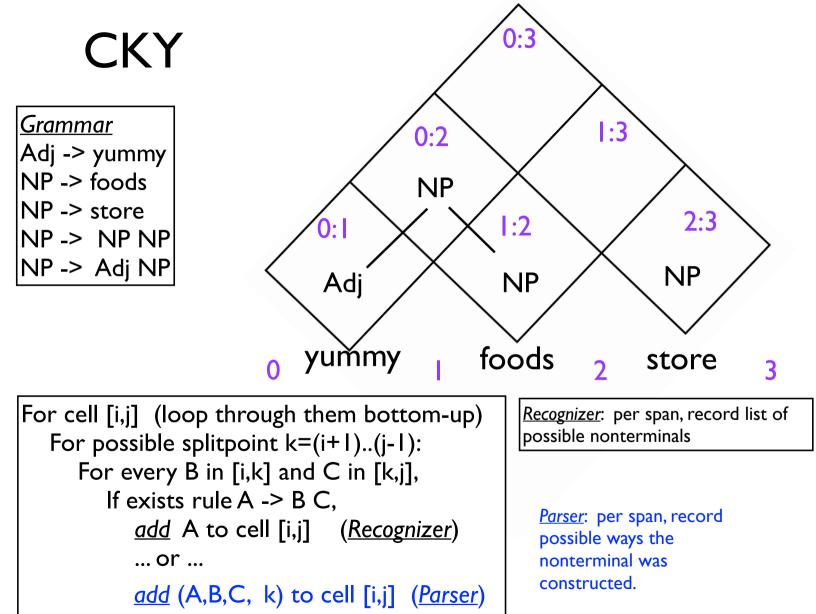
(a.k.a. binarization): always one or two RHS terms

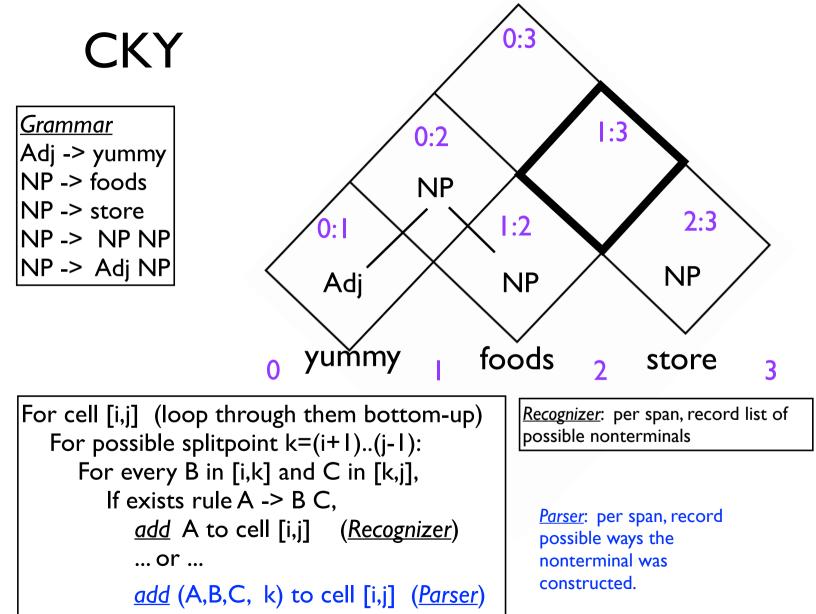


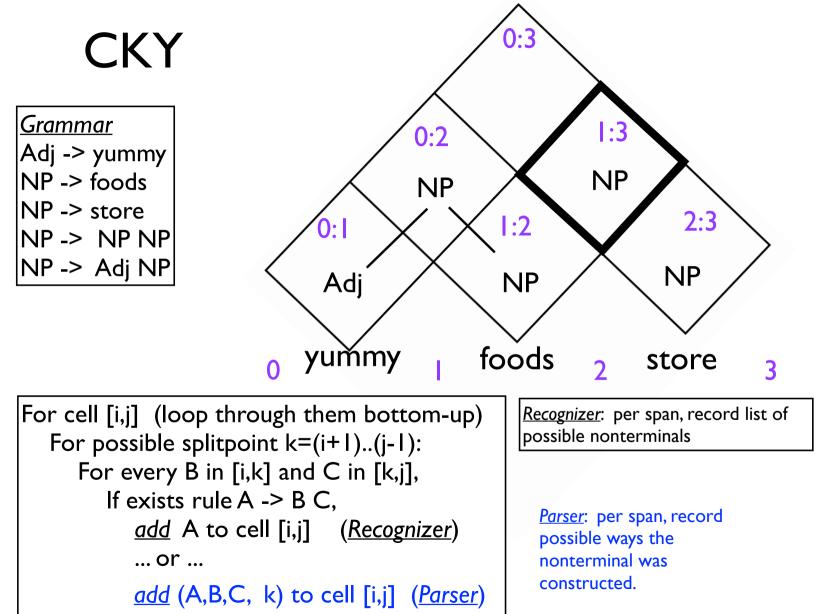


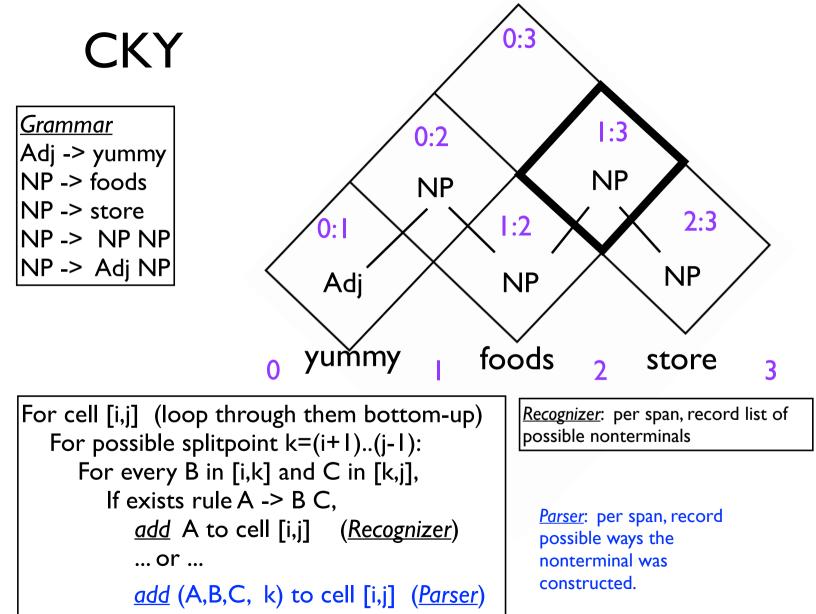


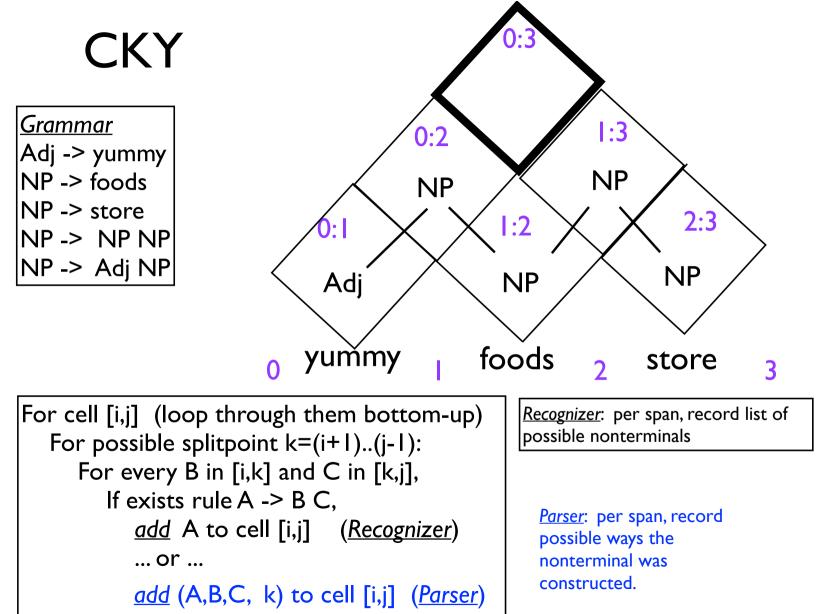


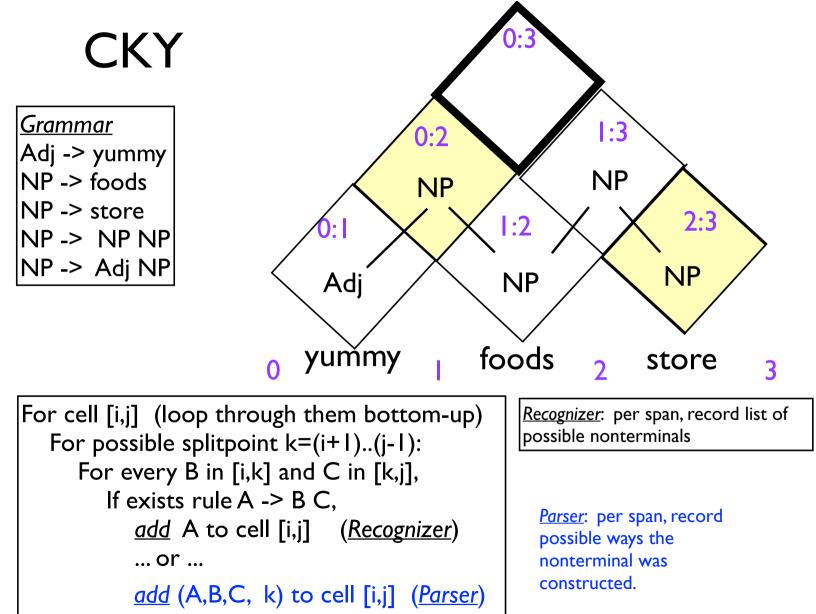


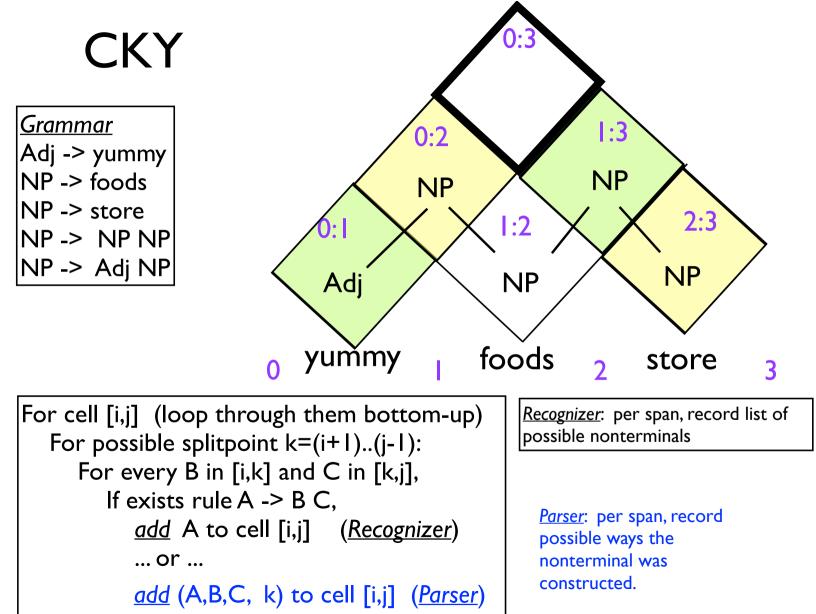


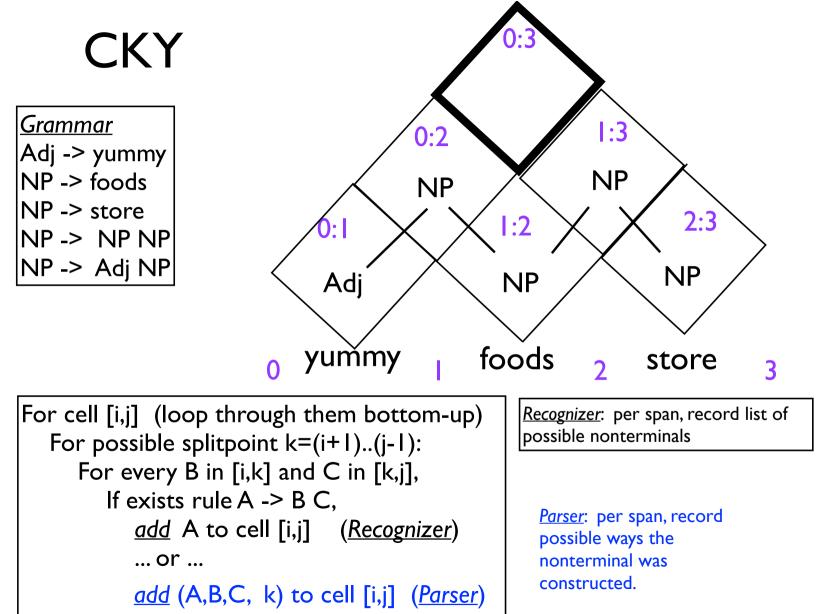


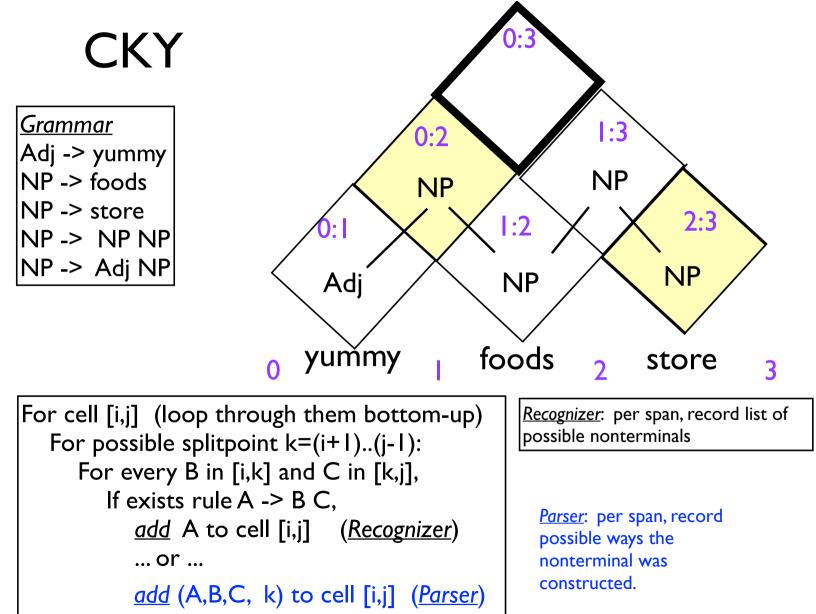


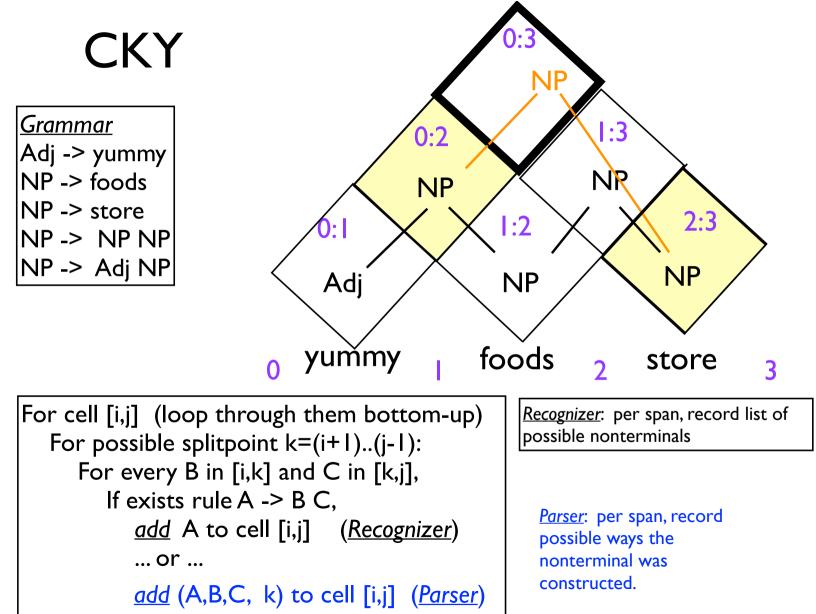


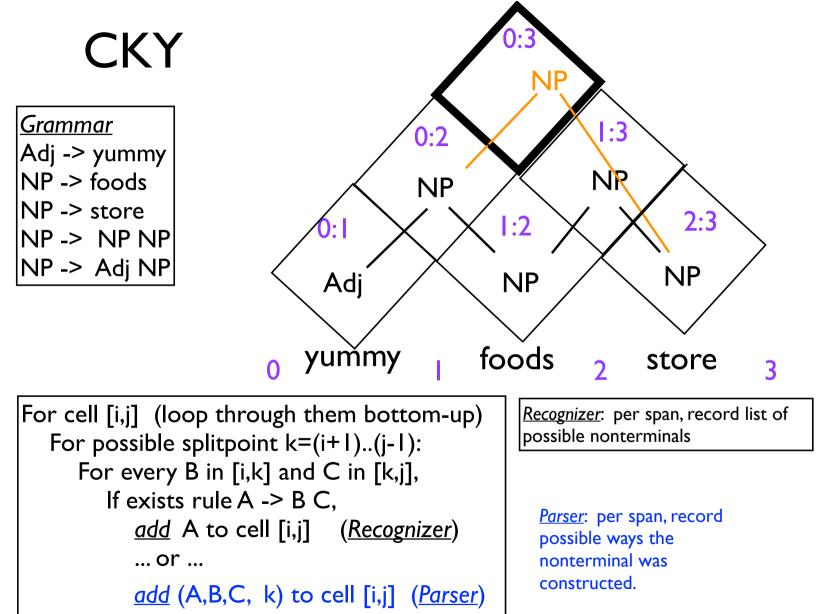


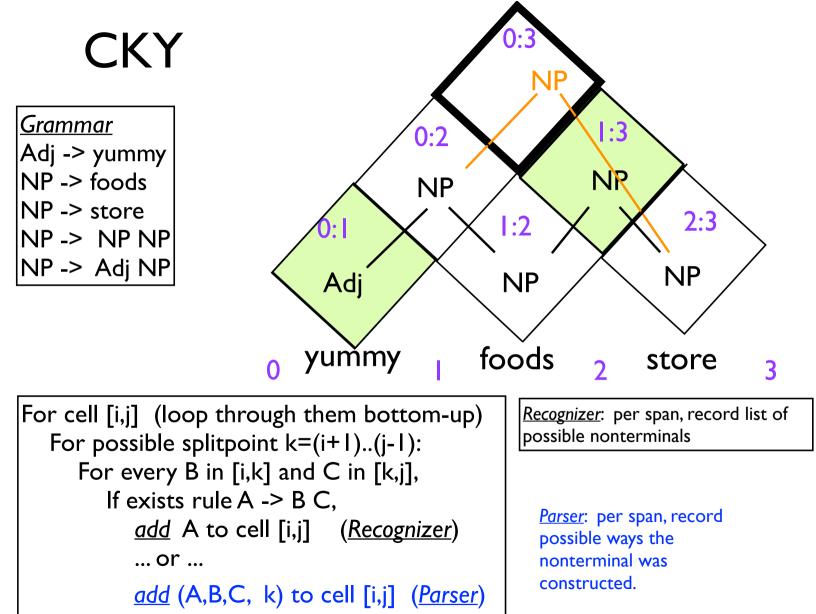


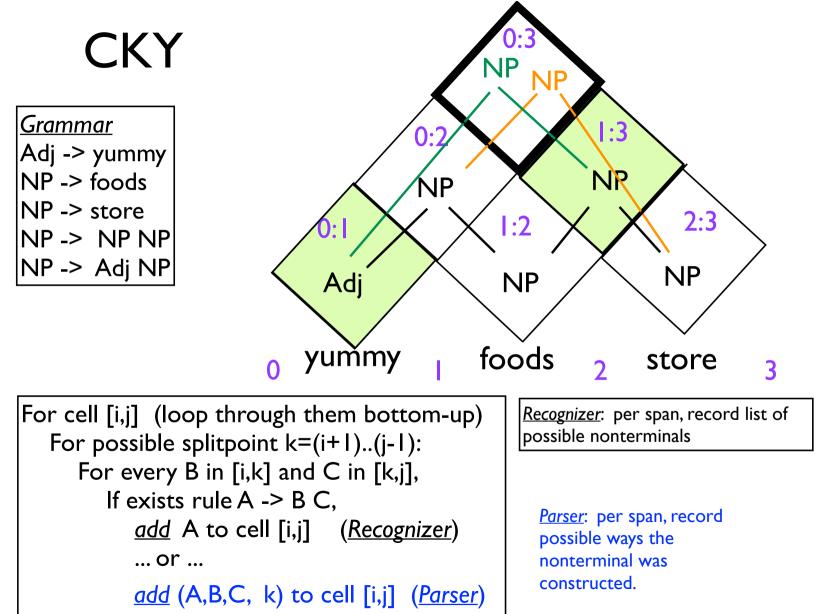


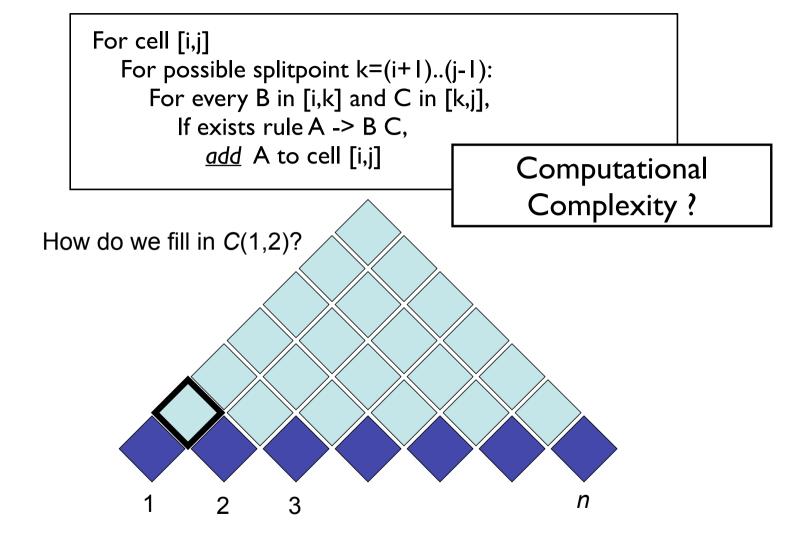


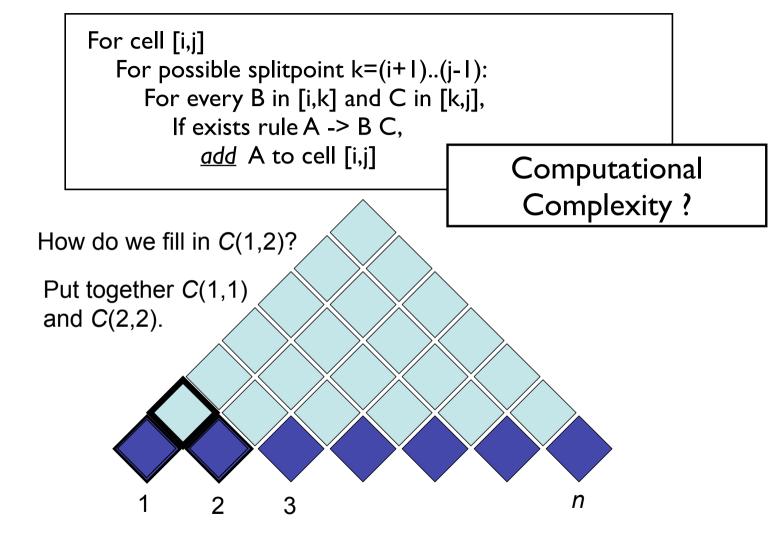


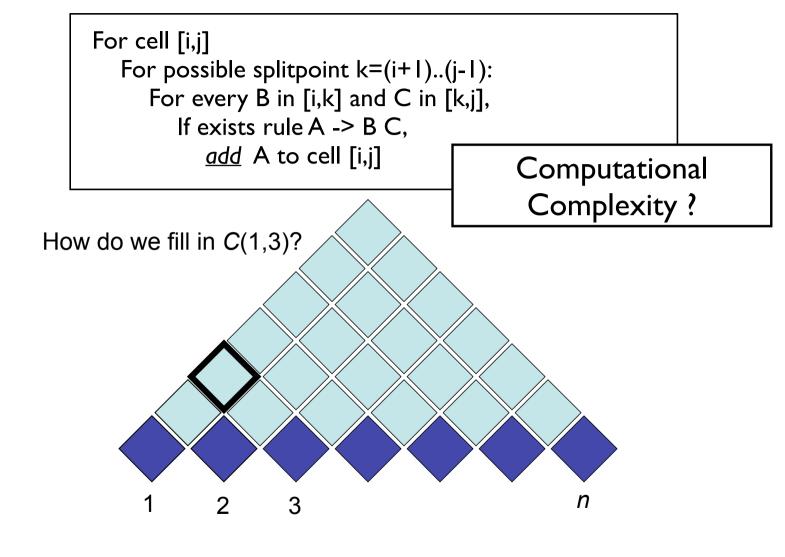


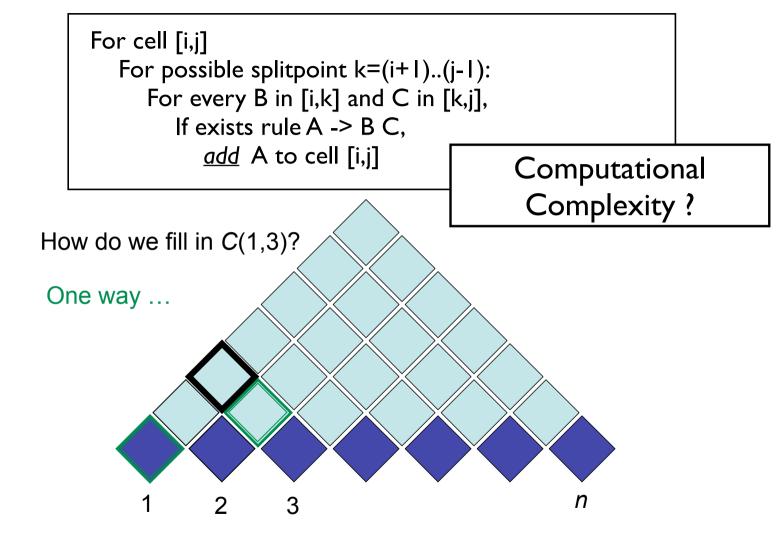


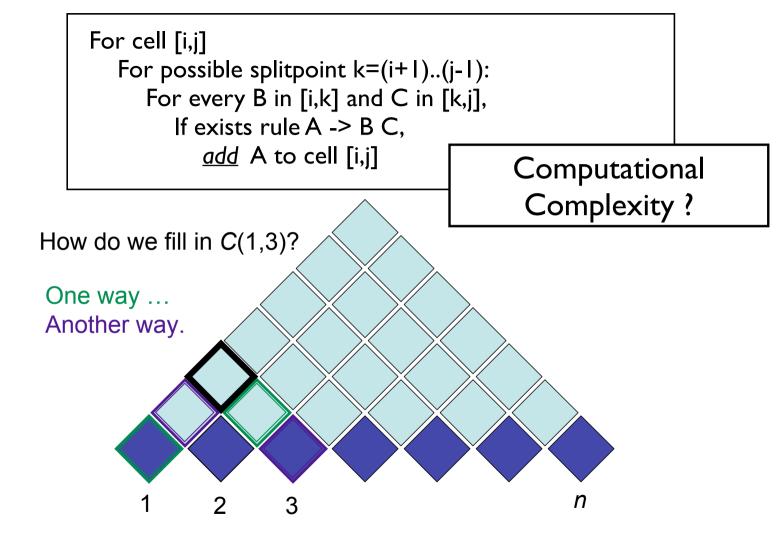


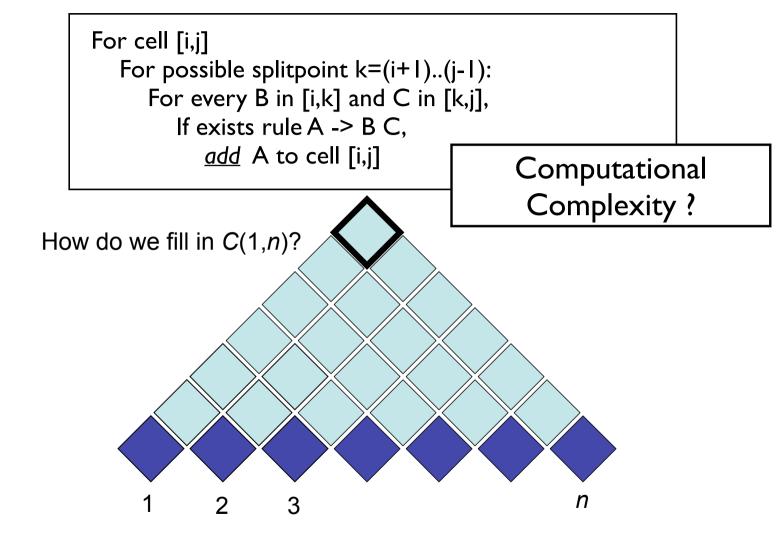


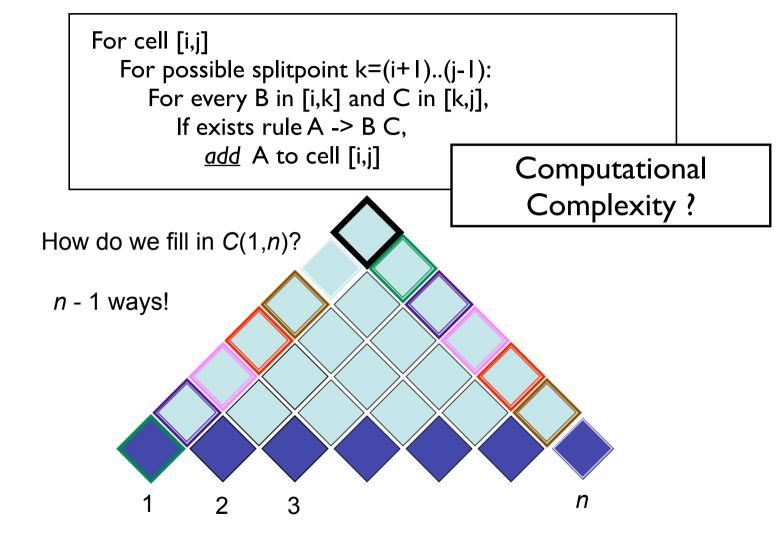


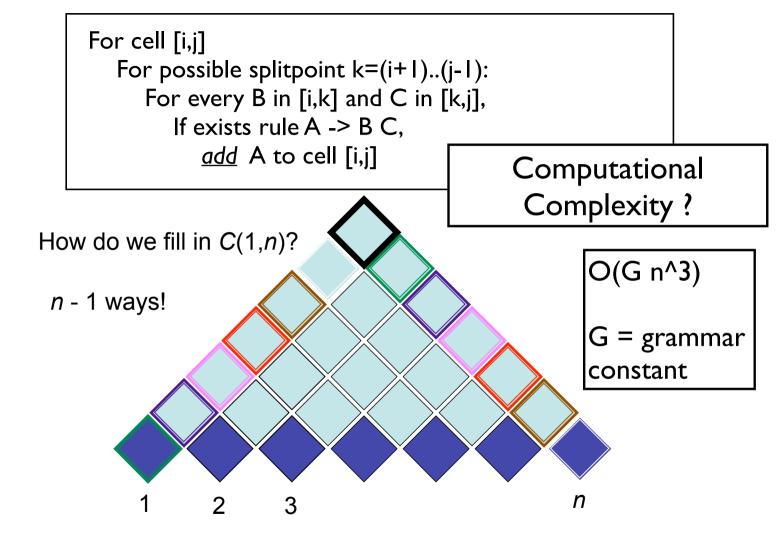












Probabilistic CFGs

- $S \rightarrow NP VP$ $Det \to that [.10] \mid a [.30] \mid the [.60]$ [.80] Noun \rightarrow book [.10] | flight [.30] $S \rightarrow Aux NP VP$ [.15] $S \rightarrow VP$ [.05] *meal* [.15] | *money* [.05] $NP \rightarrow Pronoun$ [.35] | *flights* [.40] | *dinner* [.10] $NP \rightarrow Proper-Noun$ [.30] $Verb \rightarrow book [.30] \mid include [.30]$ $NP \rightarrow Det Nominal$.20] | *prefer*; [.40] $NP \rightarrow Nominal$ [.15] *Pronoun* \rightarrow *I*[.40] | *she*[.05] Nominal \rightarrow Noun [.75] | *me* [.15] | *you* [.40] *Proper-Noun* \rightarrow *Houston* [.60] Nominal \rightarrow Nominal Noun [.20] Nominal \rightarrow Nominal PP [.05] *TWA* [.40] $Aux \rightarrow does$ [.60] | can [40] $VP \rightarrow Verb$.35] *Preposition* \rightarrow *from* [.30] | *to* [.30] $VP \rightarrow Verb NP$.20] $VP \rightarrow Verb NP PP$ [.10] on [.20] | near [.15] 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
- Extension of HMMs, strictly speaking
- (How to learn? Fully supervised with a treebank... EM for unsup...)

```
( (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
    Penn
                                   (NP (DT the) (JJ second) (NN phase) )
                                   (PP (IN of)
                                    (NP
Treebank
                                       (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) )
                                                    (, ,)
```

(P)CFG model, (P)CKY algorithm

- CKY: given CFG and sentence w
 - Does there exist at least one parse?
 - Enumerate parses (backpointers)
- Probabilistic/Weighted CKY: given PCFG and sentence w
 - Likelihood of sentence P(w)
 - Most probable parse ("Viterbi parse") argmaxy P(y | w) = argmaxy P(y, w)
 - Non-terminal span marginals (Inside-outside algorithm)
- Discriminative Tree-CRF parsing: argmaxy P(y | w)

- Parsing model accuracy: lots of ambiguity!!
 - PCFGs lack lexical information to resolve ambiguities (sneak in world knowledge?)
 - Need to add word embeddings or other lexical information to enrich phrase representations
- Parsers' computational efficiency
 - Grammar constant; pruning & heuristic search
 - O(N³) for CKY (ok? sometimes...)
 - O(N) left-to-right incremental algorithms
- Evaluate: precision and recall of labeled spans
- Treebank data

Better PCFG grammars

• Lexicalization: encode semantic preferences

Non-terminal	Direction	Priority
S	right	VP SBAR ADJP UCP NP
VP	left	VBD VBN MD VBZ TO VB VP VBG VBP ADJP NP
NP	right	N* EX \$ CD QP PRP
PP	left	IN TO FW

Table 11.3: A fragment of head percolation rules

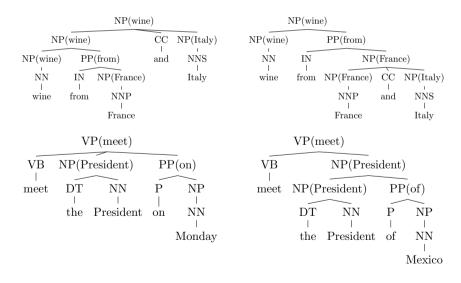


Figure 11.9: Lexicalization can address ambiguity on coordination scope (upper) and PP attachment (lower)

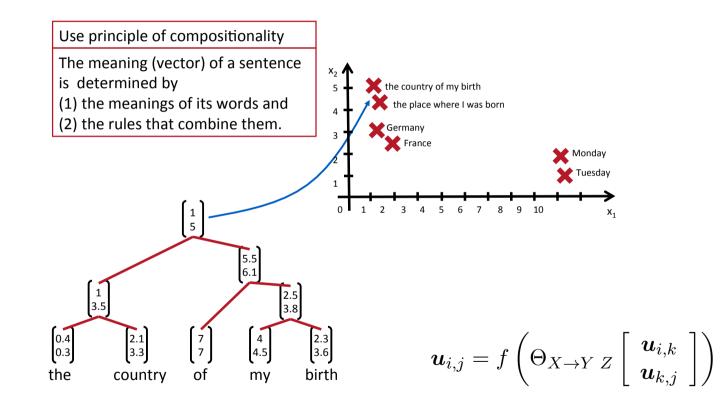
[From Eisenstein (2017)]

Reranking

- (CRF/Neural/etc.) CFGs are fast, but only use local info
- Whole-structure scoring (features, tree RNNs, etc.) is slow, but can use global info
- Solution: **Reranking**
 - CKY/Viterbi to infer top-K parses from fast CFG model
 - Score each one with NN/features for K-way multiclass problem
 - or use a ranking loss, etc.

[Socher et al. (2013)]

Reranking: TreeRNN



(Can also be used for classification or other tasks, not just parsing itself)



Model performance

Vanilla PCFG	72%
Parent-annotations (Johnson, 1998)	80%
Lexicalized (Charniak, 1997)	86%
Lexicalized (Collins, 2003)	87%
Lexicalized, reranking, self-training (McClosky et al., 2006)	92.1%
State splitting (Petrov and Klein, 2007)	90.1%
CRF Parsing (Finkel et al., 2008)	89%
TAG Perceptron Parsing (Carreras et al., 2008)	91.1%
Compositional Vector Grammars (Socher et al., 2013a)	90.4%
Neural CRF (Durrett and Klein, 2015)	91.1%

Table 11.7: Penn Treebank parsing scoreboard, circa 2015 (Durrett and Klein, 2015)

Treebanks

- Penn Treebank (constituents, English)
 - <u>http://www.cis.upenn.edu/~treebank/home.html</u>
 - Recent revisions in Ononotes
- Universal Dependencies
 - <u>http://universaldependencies.org/</u>
- Prague Treebank (syn+sem)
- many others...
- Know what you're getting!

More sophisticated formalisms

- Beyond CFGs ("Mildly context-sensitive")
 - e.g. Combinatory Categorial Grammar, Tree Adjoining Grammar, unification grammars ...
 - Extend CFGs to incorporate features to enforce grammatical constraints, or lay the groundwork for meaning interpretation
- English Resource Grammar: a hand-engineered grammar+parser
 - <u>http://erg.delph-in.net/logon</u>
 - Head-driven Phrase Structure Grammar (HPSG)
 - Parse forest -- from a CKY-like chart
 - Dependencies integrated with constituents (Next time: dep parsing as its own task)
- ML-based parsers are SOTA: coverage and resolving ambiguities

ERG

Try pressing return in this window!

