CS 6120/CS4120: Natural Language Processing

Instructor: Prof. Lu Wang
College of Computer and Information Science
Northeastern University
Webpage: www.ccs.neu.edu/home/luwang

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The grammar

S → NP VP	0.9
S → VP	0.1
VP → V NP	0.5
VP → V	0.1
VP → V @VP_V	0.3
VP → V PP	0.1
@VP_V → NP PP	1.0
NP → NP NP	0.1
NP → NP PP	0.2
NP → N	0.7
PP → P NP	1.0

N → *people*	0.5
N → *fish*	0.2
N → *tanks*	0.2
N → *rods*	0.1
V → *people*	0.1
V → *fish*	0.6
V → *tanks*	0.3
P → *with*	1.0

2

	fish 1	people 2	fish 3	tanks 4
0	score[0][1]	score[0][2]	score[0][3]	score[0][4]
1		score[1][2]	score[1][3]	score[1][4]
2			score[2][3]	score[2][4]
3				score[3][4]
4				

3

S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0

N → *people* 0.5
N → *fish* 0.2
N → *tanks* 0.2
N → *rods* 0.1
V → *people* 0.1
V → *fish* 0.6
V → *tanks* 0.3
P → *with* 1.0

	fish 1	people 2	fish 3	tanks 4
0				
1				
2				
3				
4				

4

S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0

N → *people* 0.5
N → *fish* 0.2
N → *tanks* 0.2
N → *rods* 0.1
V → *people* 0.1
V → *fish* 0.6
V → *tanks* 0.3
P → *with* 1.0

	fish 1	people 2	fish 3	tanks 4
0	N → fish 0.2 V → fish 0.6			
1		N → people 0.5 V → people 0.1		
2			N → fish 0.2 V → fish 0.6	
3				N → tanks 0.2 V → tanks 0.3
4				

5

S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
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N → *people* 0.5
N → *fish* 0.2
N → *tanks* 0.2
N → *rods* 0.1
V → *people* 0.1
V → *fish* 0.6
V → *tanks* 0.3
P → *with* 1.0

	fish 1	people 2	fish 3	tanks 4
0	N → fish 0.2 V → fish 0.6 NP → N 0.14 VP → V 0.06 S → VP 0.006			
1		N → people 0.5 V → people 0.1 NP → N 0.35 VP → V 0.01 S → VP 0.001		
2			N → fish 0.2 V → fish 0.6 NP → N 0.14 VP → V 0.06 S → VP 0.006	
3				N → tanks 0.2 V → tanks 0.3 NP → N 0.14 VP → V 0.03 S → VP 0.003
4				

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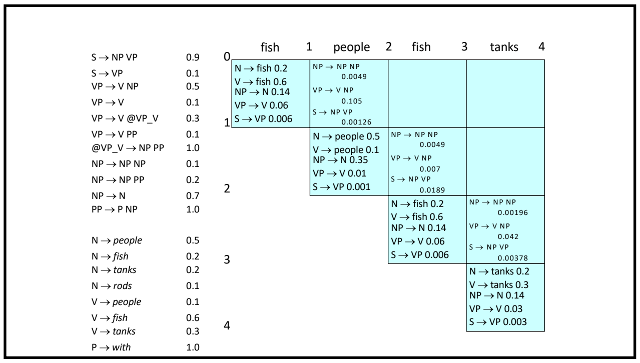
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VP → V NP 0.5
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VP → V @VP_V 0.3
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@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.0049
VP → V NP 0.105
S → NP VP 0.00126
N → people 0.5
V → people 0.1
NP → N 0.35
VP → V 0.01
S → VP 0.001
NP → NP NP 0.0049
VP → V NP 0.007
S → NP VP 0.0189
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.00196
VP → V NP 0.042
S → NP VP 0.00378
N → tanks 0.2
V → tanks 0.3
NP → N 0.14
VP → V 0.03
S → VP 0.003

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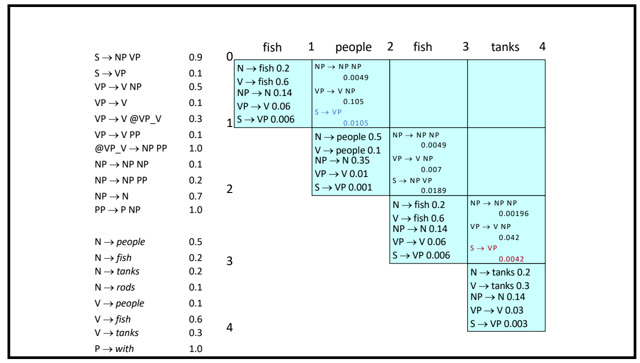
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S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.0049
VP → V NP 0.105
S → VP 0.0105
N → people 0.5
V → people 0.1
NP → N 0.35
VP → V 0.01
S → VP 0.001
NP → NP NP 0.0049
VP → V NP 0.007
S → NP VP 0.0189
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.00196
VP → V NP 0.042
S → VP 0.0042
N → tanks 0.2
V → tanks 0.3
NP → N 0.14
VP → V 0.03
S → VP 0.003

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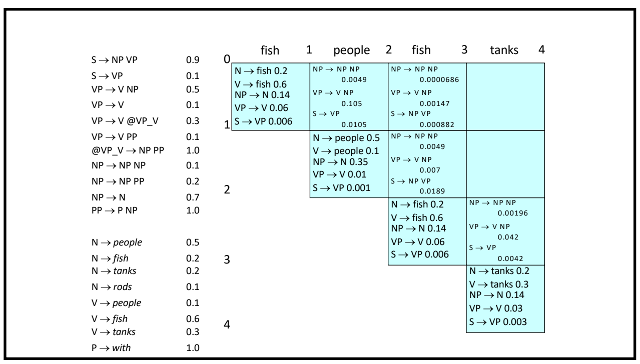
S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.0049
VP → V NP 0.105
S → VP 0.0105
NP → NP NP 0.0000686
VP → V NP 0.00147
S → NP VP 0.000882
N → people 0.5
V → people 0.1
NP → N 0.35
VP → V 0.01
S → VP 0.001
NP → NP NP 0.0049
VP → V NP 0.007
S → NP VP 0.0189
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.00196
VP → V NP 0.042
S → VP 0.0042
N → tanks 0.2
V → tanks 0.3
NP → N 0.14
VP → V 0.03
S → VP 0.003

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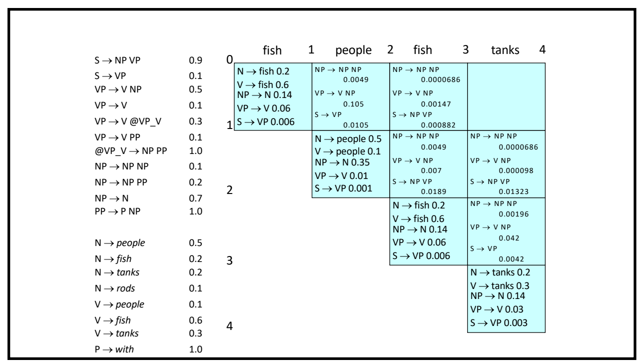
S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.0049
VP → V NP 0.105
S → VP 0.0105
NP → NP NP 0.0000686
VP → V NP 0.00147
S → NP VP 0.000882
N → people 0.5
V → people 0.1
NP → N 0.35
VP → V 0.01
S → VP 0.001
NP → NP NP 0.0049
VP → V NP 0.007
S → NP VP 0.0189
NP → NP NP 0.0000686
VP → V NP 0.000098
S → NP VP 0.01323
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.00196
VP → V NP 0.042
S → VP 0.0042
N → tanks 0.2
V → tanks 0.3
NP → N 0.14
VP → V 0.03
S → VP 0.003

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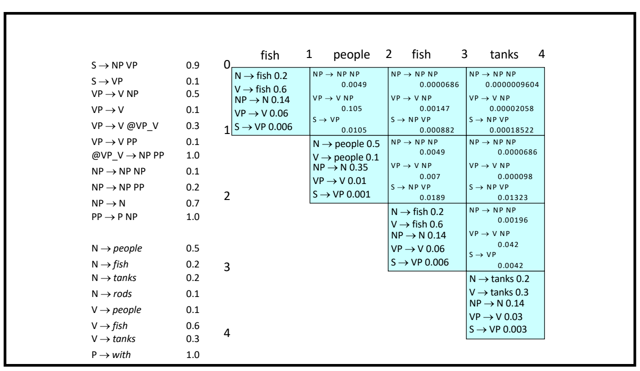
S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.0049
VP → V NP 0.105
S → VP 0.0105
NP → NP NP 0.0000686
VP → V NP 0.00147
S → NP VP 0.000882
NP → NP NP 0.0000009604
VP → V NP 0.00002058
S → NP VP 0.00018522
N → people 0.5
V → people 0.1
NP → N 0.35
VP → V 0.01
S → VP 0.001
NP → NP NP 0.0049
VP → V NP 0.007
S → NP VP 0.0189
NP → NP NP 0.0000686
VP → V NP 0.000098
S → NP VP 0.01323
N → fish 0.2
V → fish 0.6
NP → N 0.14
VP → V 0.06
S → VP 0.006
NP → NP NP 0.00196
VP → V NP 0.042
S → VP 0.0042
N → tanks 0.2
V → tanks 0.3
NP → N 0.14
VP → V 0.03
S → VP 0.003

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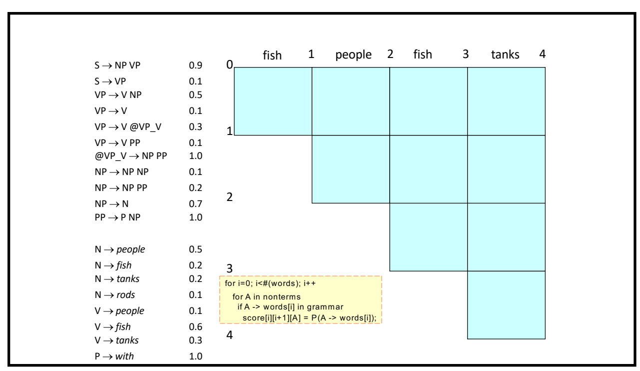
S → NP VP 0.9
S → VP 0.1
VP → V NP 0.5
VP → V 0.1
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
NP → N 0.7
PP → P NP 1.0
N → people 0.5
N → fish 0.2
N → tanks 0.2
N → rods 0.1
V → people 0.1
V → fish 0.6
V → tanks 0.3
P → with 1.0
0 fish 1 people 2 fish 3 tanks 4
for i=0; i<#(words); i++
for A in nonterms
if A -> words[i] in grammar
score[i][i+1][A] = P(A -> words[i]);

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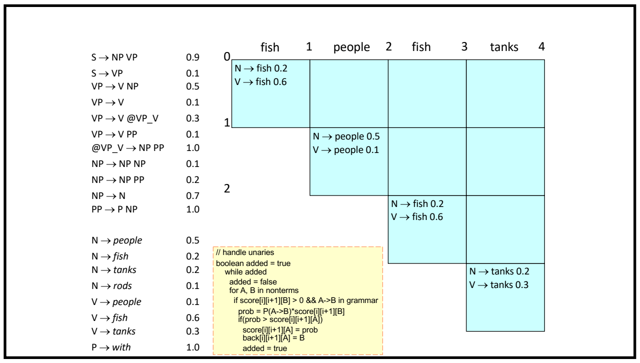

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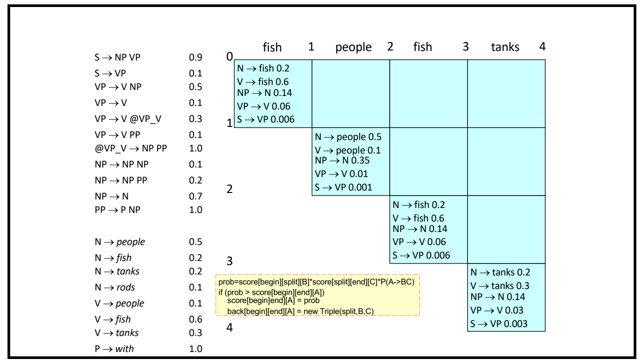

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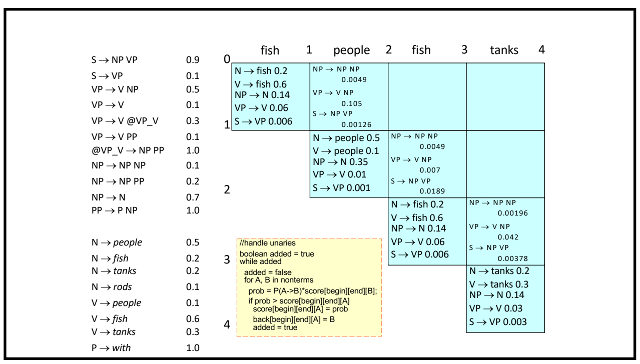

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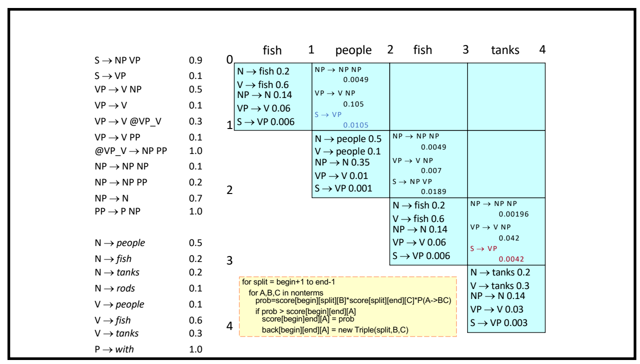

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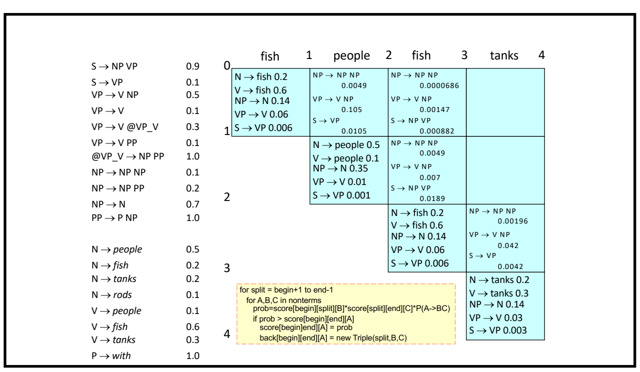

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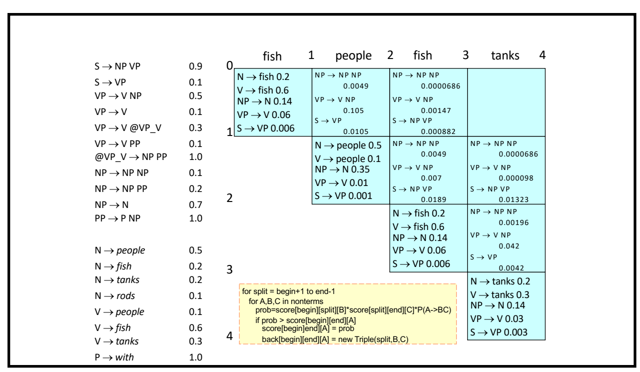

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Rule	Prob.
S → NP VP	0.9
S → VP	0.1
VP → V NP	0.5
VP → V	0.1
VP → V @VP_V	0.3
VP → V PP	0.1
@VP_V → NP PP	1.0
NP → NP NP	0.1
NP → NP PP	0.2
NP → N	0.7
PP → P NP	1.0
N → *people*	0.5
N → *fish*	0.2
N → *tanks*	0.2
N → *rods*	0.1
V → *people*	0.1
V → *fish*	0.6
V → *tanks*	0.3
P → *with*	1.0

	fish (0–1)	people (1–2)	fish (2–3)	tanks (3–4)
0	N → fish 0.2 V → fish 0.6 NP → N 0.14 VP → V 0.06 S → VP 0.006	NP → NP NP 0.0049 VP → V NP 0.105 S → VP 0.0105	NP → NP NP 0.0000686 VP → V NP 0.00147 S → NP VP 0.000882	NP → NP NP 0.0000009604 VP → V NP 0.00002058 S → NP VP 0.00018522
1		N → people 0.5 V → people 0.1 NP → N 0.35 VP → V 0.01 S → VP 0.001	NP → NP NP 0.0049 VP → V NP 0.007 S → NP VP 0.0189	NP → NP NP 0.0000686 VP → V NP 0.000098 S → NP VP 0.01323
2			N → fish 0.2 V → fish 0.6 NP → N 0.14 VP → V 0.06 S → VP 0.006	NP → NP NP 0.00196 VP → V NP 0.042 S → VP 0.0042
3				N → tanks 0.2 V → tanks 0.3 NP → N 0.14 VP → V 0.03 S → VP 0.003
4				

Call buildTree(score, back) to get the best parse

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Extended CKY parsing

- CKY parsing is usually done **after binarization**
- Unaries can be incorporated into the algorithm
  - Messy, but doesn't increase algorithmic complexity
- Empties can be incorporated
  - Doesn't increase complexity; essentially like unaries
- Binarization is *vital*
  - Without binarization, you don't get parsing cubic in the length of the sentence and in the number of nonterminals in the grammar

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Where to learn the probabilities: Treebanks

- English Penn Treebank: Standard corpus for testing syntactic parsing consists of 1.2 M words of text from the Wall Street Journal (WSJ).
- Typical to train on about 40,000 parsed sentences and test on an additional standard disjoint test set of 2,416 sentences.
- Chinese Penn Treebank: 100K words from the Xinhua news service.
- Other corpora existing in many languages, see the Wikipedia article "Treebank"

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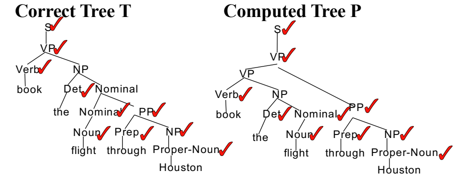
Computing Evaluation Metrics



\# Constituents: 12   # Constituents: 12

\# Correct Constituents: 10

Recall = 10/12= 83.3%   Precision = 10/12=83.3% F_1 = 83.3%

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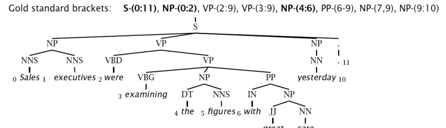
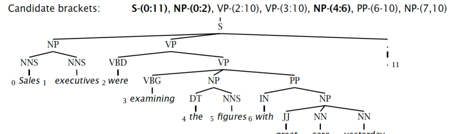
Evaluating constituency parsing

Gold standard brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)



Candidate brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)



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Evaluating constituency parsing

Gold standard brackets:

S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)

Candidate brackets:

S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

Labeled Precision	3/7 = 42.9%
Labeled Recall	3/8 = 37.5%
LP/LR F1	40.0%
POS Tagging Accuracy	11/11 = 100.0%

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How good are PCFGs?

- Penn WSJ parsing accuracy: about 73% LP/LR F1 with feature-based models (state-of-the-art neural model is 91-92% F1)
- Robust
  - Usually admit everything, but with low probability
- Partial solution for grammar ambiguity
  - A PCFG gives some idea of the plausibility of a parse

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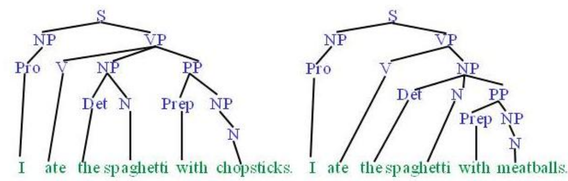

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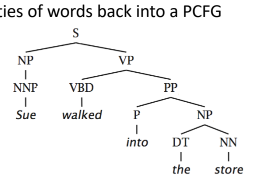
(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

- The head word of a phrase gives a good representation of the phrase's structure and meaning (*head words are decided by rules, the most important word in a constituent*)
- Puts the properties of words back into a PCFG



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Head Words

- Syntactic phrases usually have a word in them that is most "central" to the phrase.
- Linguists have defined the concept of a lexical **head** of a phrase.
- Simple rules can identify the head of any phrase by percolating head words up the parse tree.
  - Head of a VP is the main verb
  - Head of an NP is the main noun
  - Head of a PP is the preposition
  - Head of a sentence is the head of its VP

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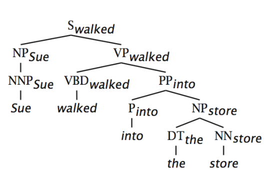
(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

- The head word of a phrase gives a good representation of the phrase's structure and meaning
- Puts the properties of words back into a PCFG



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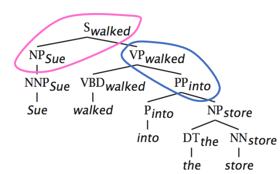
(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

- The head word of a phrase gives a good representation of the phrase's structure and meaning
- Puts the properties of words back into a PCFG



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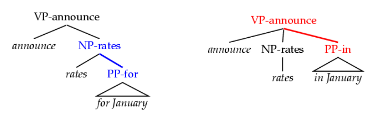
(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

- Word-to-word affinities are useful for certain ambiguities
  - PP attachment is now (partly) captured in a local PCFG rule.



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Lexicalized parsing was seen as *the* parsing breakthrough of the late 1990s

- Eugene Charniak, 2000 JHU workshop: “To do better, it is necessary to condition probabilities on the actual words of the sentence. This makes the probabilities much tighter:
  - *p*(VP → V NP NP) = 0.00151
  - *p*(VP → V NP NP | said) = 0.00001
  - *p*(VP → V NP NP | gave) = 0.01980 ” *p(rule|head word)*
- Michael Collins, 2003 COLT tutorial: “**Lexicalized Probabilistic Context-Free Grammars** … perform vastly better than PCFGs (88% vs. 73% accuracy)”

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Lexicalization models argument selection by sharpening rule expansion probabilities

- The probability of different verbal complement frames (i.e., “subcategorizations”) depends on the verb:

Local Tree	*come*	*take*	*think*	*want*
VP → V	9.5%	2.6%	4.6%	5.7%
VP → V NP	1.1%	**32.1%**	0.2%	13.9%
VP → V PP	**34.5%**	3.1%	7.1%	0.3%
VP → V SBAR	6.6%	0.3%	**73.0%**	0.2%
VP → V S	2.2%	1.3%	4.8%	**70.8%**
VP → V NP S	0.1%	5.7%	0.0%	0.3%
VP → V PRT NP	0.3%	5.8%	0.0%	0.0%
VP → V PRT PP	6.1%	1.5%	0.2%	0.0%

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Human Parsing

- Computational parsers can be used to predict human reading time as measured by tracking the time taken to read each word in a sentence.
- Psycholinguistic studies show that words that are more probable given the preceding lexical and syntactic context are read faster.
  - John put the dog in the pen with a lock.
  - John liked the dog in the pen with a bone.
- Modeling these effects requires an ***incremental*** statistical parser that incorporates one word at a time into a continuously growing parse tree.

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Garden Path Sentences

- People are confused by sentences that seem to have a particular syntactic structure but then suddenly violate this structure, so the listener is “lead down the garden path”.
  - The horse raced past the barn fell.
    - vs. The horse raced past the barn broke his leg.
  - The complex houses married students.
  - The old man the sea.
  - While Anna dressed the baby spit up on the bed.
- Incremental computational parsers can try to predict and explain the problems encountered parsing such sentences.

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Center Embedding

- Nested expressions are hard for humans to process beyond 1 or 2 levels of nesting.
  - The rat the cat chased died.
  - The rat the cat the dog bit chased died.
  - The rat the cat the dog the boy owned bit chased died.
- Requires remembering and popping incomplete constituents from a stack and strains human short-term memory.
- Equivalent “tail embedded” (tail recursive) versions are easier to understand since no stack is required.
  - The boy owned a dog that bit a cat that chased a rat that died.

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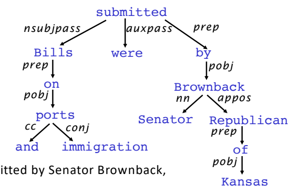
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations ("arrows") called dependencies

The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc.)



Bills on ports and immigration were submitted by Senator Brownback, Republican of Kansas.

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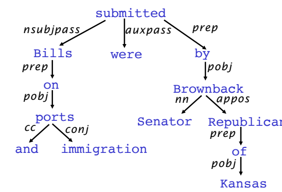
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations ("arrows") called dependencies

The arrow connects a head (governor, superior, regent) with a dependent (modifier, inferior, subordinate)

Usually, dependencies form a tree (connected, acyclic, single-head)



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Relation between phrase structure and dependency structure

- A dependency grammar has a notion of a head. Officially, CFGs don't.
- But modern linguistic theory and all modern statistical parsers (Charniak, Collins, Stanford, …) do, via hand-written phrasal "head rules":
  - The head of a Noun Phrase is a noun/number/adj/…
  - The head of a Verb Phrase is a verb/modal/….
- The head rules can be used to extract a dependency parse from a CFG parse

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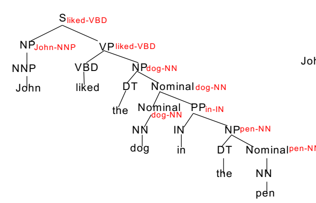
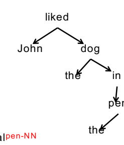
Dependency Graph from Parse Tree

- Can convert a phrase structure parse to a dependency tree by making the head of each non-head child of a node depend on the head of the head child.





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